RESEARCH

UDOT Keeping Utah Moving

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IMPACT OF SHARED AUTONOMOUS VEHICLES ON VEHICLE MILES TRAVELED IN UTAH

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Autonomous Vehicles (AVs) can provide benefits and flexibility leading to significant reductions in the generalized cost of travel and, potentially, more demand for travel. The combination of the AV technology with Mobility as a Service (MaaS) will create a new disruptive transportation mode – Shared Autonomous Vehicles (SAVs) that have the promise to re-define the transportation landscape by improving mobility and competing with conventional transportation modes. While it is foreseen that SAVs could potentially be on the market in a decade or two, long range transportation planning in Utah to date has not accounted for its impact. This study fills this gap by investigating the impact of SAVs on travel patterns in Utah for the 2040 horizon year. The Wasatch Front (WF) travel demand model is used to estimate the impact of SAVs on Vehicle Miles Traveled (VMT). Twelve scenarios consisting of different combinations of trip growth rates and SAV competitiveness were developed and analyzed to estimate a range for VMT increase with the introduction of SAV. Results revealed that SAVs will increase the total number of trips by 1% to 7% across designed scenarios. Moreover, SAVs can shift mode shares away from conventional transportation modes. Finally, it is estimated that SAVs will increase daily VMT by 4% to 9% across designed scenarios due to both improved mobility of underserved populations and additional repositioning trips.</td></tr>
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LIST OF ACRONYMS

ACS	American Community Survey
AV	Autonomous Vehicle
CPS	Current Population Survey
SAV	Shared Autonomous Vehicle
VMT	Vehicle Miles Traveled
LC	Life Cycle
TAZ	Transportation Analysis Zones
TNC	Transportation Network Company
BRT	Bus Rapid Transit
WFRC	Wasatch Front Regional Council
MAG	Mountainland Association of Governments
UDOT	Utah Department of Transportation
MaaS	Mobility as a Service
SAE	Society of Automotive Engineer
DRS	Dynamic Ride Sharing
MPO	Metropolitan Planning Organization
LR	Light Rail
NHTS	National Household Travel Survey
NHTSA	National Highway Traffic Safety Administration
MNL	Multinomial Logit
VKT	Vehicle Kilometers Traveled
UTA	Utah Transit Authority

WTP Willingness to Pay

CBD Central Business District

HBW Home-Based Work

HBC Home-Based College

HBOth Home-Based Other

HBSch Home-Based School

HBShp Home-Based Shopping

NHBW Non-Home-Based Work

NHBNW Non-Home-Based Non-Work

TRR Trip Reduction Rate

EXECUTIVE SUMMARY

It is anticipated that ongoing advancement of computational capabilities will make it possible to build Autonomous Vehicles (AVs) with a high level of reliability operating under various complex situations. AVs can provide travelers with additional benefits and flexibility reducing the cost of travel, which, in turn, may lead to increased travel demand. In conjunction with the growth of AV technology is an evolving transportation service – Mobility as a Service (MaaS) – which can be seen in today's Transportation Network Companies. Combining the AV technology with MaaS creates a new transportation mode – Shared Autonomous Vehicles (SAVs) -- that has the promise to re-define the transportation landscape by generating more trips and by competing with conventional transportation modes. While it is foreseen that SAVs could potentially be on the market in a decade or two, Metropolitan Planning Organizations (MPOs) and Departments of Transportation (DOTs) are just beginning to estimate the impacts of SAVs on travel behavior. This research fills this gap by investigating the impact of SAVs on travel demand in Utah in the 2040 horizon year.

In this project, we modified the Wasatch Front (WF) travel demand model to estimate the impact of SAVs on Vehicle Miles Traveled (VMT). These model modifications were made in the trip generation and mode choice modules of the WF travel model. To address the impact of SAVs on trip generation, we adjusted the mobility of seniors, people with disabilities or driving-restrictive medical conditions, and children, demographics that often encounter challenges traveling independently. The research assumes that SAVs will improve the mobility of these populations for non-work and non-school trips. To accommodate SAVs in the mode choice module, a new mode – MaaS -- is added within the motorized branch. The attractiveness of the MaaS mode – as expressed in a utility function -- is calculated based on the burden of in-vehicle-time, initial pick-up time, and operating cost. In order to model the additional benefits and flexibility that SAVs offer, we reduced the generalized cost of this mode compared to conventional transportation modes. Finally, 12 scenarios are designed and analyzed to investigate the impact of various combinations of trip growth and SAV market penetrations on VMT.

Results revealed that SAVs can increase the total number of trips by a range from 1% to 7% across designed scenarios. Comparing mode shares across scenarios showed that while SAVs can shift mode shares from all conventional transportation modes it competes most effectively with auto and non-motorized modes. Higher mode shifts were found for SAV shared ride modes when compared to SAV ride alone, partially due to Utah's demographics, with larger average household sizes.

Analysis of modal shifts by trip purpose showed that for all trip purposes except Nonhome-Based (NHB) trips, SAVs compete more with auto and non-motorized modes. For NHB trips, transit experiences the largest mode shift to SAVs. Among available transit modes, Bus, BRT, and Light Rail are estimated to experience the highest degree of shift to MaaS. An analysis of trip length distributions revealed that the SAV mode is more desirable for shorter trips than longer ones. Moreover, while reducing the generalized cost of SAVs makes it more competitive for longer trips, it does not significantly impact the share of SAVs for shorter trips. Eventually, it is observed that SAV increases daily VMT by 4% to 9% across designed scenarios due to both improved mobility of underserved population and additional VMT from the repositioning of vehicles towards the next rider.

1. INTRODUCTION

1.1 Problem Statement

Recent advancement of computational capabilities in terms of hardware, algorithms, communication architecture, sensing, and navigation devices has made it possible to build Autonomous Vehicles (AVs) with a high level of reliability, operating in complex driving situations. The Society of Automotive Engineers (SAE) International, building upon the earlier work of the National Highway Traffic Safety Administration (NHTSA), has defined automation levels from 0 to 5[1].

Level 5 vehicles will have the maximum level of automation and can be operated without a driver under all roadway and environmental conditions (Miller, et al., 2014). Vehicles with lower levels of automation are currently available, equipped with different automation features such as adaptive cruise control, lane-keeping systems, and parking assistance, etc. Since 2009, Google reported over 5 million miles driven with AVs, mostly on public roads, and expects to introduce a commercialized self-driving vehicle around mid-2018 (Lee, 2017). Moreover, most of the major automobile manufacturers including General Motors (LeBeau, 2013), Mercedes-Benz (Andersson, 2013), Nissan (Nissan Motor Company, 2013), and Volvo (Carter, 2012), target to sell vehicles with automated driving features by 2020. Although fully automated vehicles are not currently available for purchase, it is foreseen that they could potentially be on the market in a decade or two (Levin and Boyles, 2015).

In addition, the number of states in the U.S. considering legislation related to AVs is gradually increasing every year. In 2017, 33 states had introduced legislation and 21 states had passed legislation related to AVs. While current regulations in most places require the presence of a driver behind the steering wheel to take control of the vehicle in case of an emergency, it is

[1] In a Level 0 vehicle, the driver is responsible for the primary vehicle controls (brake, steering, and motive power) and also monitoring the road and operation of all other vehicles at all times. Level 1 automation provides function-specific features such as anti-lock braking. Level 2 automation allows drivers to cede primary control in certain situations, but the driver is still expected to monitor vehicle actions and take over driving without advance warning. In Level 3 vehicles, the car has greater responsibility for monitoring the traffic and environmental conditions. In this level, the car is expected to alert the driver if transition in control is needed. Level 4 vehicles provide similar features as Level 3, but they do not require the driver’s attention for safety. Self-driving in Level 4 vehicles is only supported in limited areas or under special circumstances. Level 5 vehicles have the maximum level of automation and can be operated without a driver under all roadway and environmental conditions (Miller et al., 2014).

likely that such requirements might change in the near future (Autonomous Vehicles, 2018). Therefore, AVs might be available within the time frame when most of the Metropolitan Planning Organizations (MPOs) and Departments of Transportation (DOTs) consider their long-range transportation plans.

AVs can provide travelers with additional benefits and flexibility. For instance, travelers are able to engage in various activities such as reading, playing video games, and sending emails while traveling. They may also have AVs drop them off at their destinations then park elsewhere to avoid paying for parking (Levin and Boyles, 2015). AVs might have the potential to increase the mobility of children, seniors, and people with driving-restrictive medical conditions by eliminating human involvement during driving (Harper et al., 2016). Moreover, AVs could substantially reduce the number of crashes due to various human errors such as slow reaction time, speeding, driving under the influence, and inexperience. These benefits could lead to a significant reduction in the cost of travel, and subsequently more demand for travel and a modal shift away from public transport, passenger trains, and air (Wadud et al., 2016).

While the ownership of AVs can be a big fixed cost, another stream of research has been focusing on combining AVs with Mobility-as-a-Service (MaaS). MaaS presents people with different mobility options, reducing or eliminating the need to own a private vehicle. It is also referred to as shared mobility in certain contexts, and can come in various forms, such as personal vehicle sharing, bikesharing, carpooling, vanpooling, ridesourcing and ride-hailing. Ridesourcing and ridehailing are typically served by Transportation Network Companies (TNCs), leveraging smartphone apps to connect drivers with passengers. Passengers book a car through the app to take them to their desired destinations.

Combining AV technology with MaaS creates a new mode – Shared Autonomous Vehicles (SAVs), which could provide inexpensive and flexible on-demand service. SAVs may operate on the TNC model, enabling travelers to obtain a ride through a smartphone app. SAVs can also relocate themselves to a more favorable location with lower parking cost and higher demand. These advances may provide environmental benefits in terms of reduced parking and vehicle ownership needs. However, there are potential downsides of such services. For instance, the inexpensive cost of this new mobility service could result in more trips and, in turn, higher VMT. It could also cause modal shifts from conventional public transit. Moreover, travelers could walk less due to the convenience of on-demand mobility services, with adverse health effects. Consequently, while SAVs might have substantial positive impacts in terms of improving safety, efficiency, accessibility, and mobility, it could also induce greater travel demand and modal shift from public transport and active transportation modes.

Although there is a close analogy between the SAV and today's TNC mode, there is a key distinguishing factor – that is, since SAV is driverless, its operating cost will be reduced, increasing its cost effectiveness.

Considering additional benefits and flexibility that SAV offers, it has the promise to re-define the transportation landscape as we know it. To date, long-range transportation planning in the state of Utah has not formally accounted for the impact of SAV technology. Consequently, there is a need for research to provide useful insight into the impact of SAV on travel behaviors.

1.2 Objectives

The primary objective of this study is to estimate the impact of SAVs on VMT in Utah in the year 2040 forecast horizon. The results of this research will assist UDOT and WFRC to understand the impact of SAVs on travel patterns in terms of increased trip generation and shift from traditional modes of travel.

1.3 Scope

The primary tool used to explore the impact of SAVs on VMT in Utah is the Wasatch Front (WF) Travel Demand Model, a traditional four-step regional travel model. This modeling framework enables the research team to investigate key impacts of SAVs on trip generation and mode split. However, there are limitations to the detail in the WF model that the project team acknowledges which may, in turn, influence how the SAV technology will affect travel in Utah. We discuss these limitations in the Conclusions section of the report.

1.4 Outline of Report

This report documents the findings of the research and proceeds with the following sections:

- Literature Review
- Research Methods - including a discussion on modifications to the Trip Generation and Mode Choice Models
- Results and Findings
- Conclusion

2. LITERATURE REVIEW

2.1 Overview

This research is based on the premise that SAVs will increase mobility for specific demographic populations while also resulting in a new mode that will “compete” for trips with other modes, including automobile, transit (commuter and light rails, bus) and the non-motorized modes. Further, the key analytical tool used to explore the impact of SAVs on VMT in Utah is the Wasatch Front Travel Demand Model. Consequently, the literature review conducted for this research focuses on the following areas:

- Efforts to Model SAVs Using Travel Demand Models
- Impacts of SAVs on Underserved Populations
- Related Demographic Trends in the Wasatch Front Area
- Market Acceptance of SAVs
- Availability of SAVs by Land-Use Type

2.2 Efforts to Model SAVs Using Travel Demand Models

In recent years, there has been increased research interest in the area of AVs. AVs combined with MaaS has the promise to re-define the transportation landscape as we know it. However, much of the literature on AVs has been focusing on the technological hurdles in placing AVs safely on the road. In this research synthesis, we attempt to provide a comprehensive summary on recent research efforts to investigate the impacts of AVs (or SAVs) using travel-demand modeling techniques.

Previous studies mostly focused on four-step planning models and, more recently, activity-based models, to explore the impact of AVs (Levin and Boyles, 2015). The main advantage of activity-based models when compared with traditional four-step models lies in their capability to predict repositioning trips. However, many practitioners prefer to use four-step models due to the additional data and computational resource requirements of activity-based modeling.

Levin and Boyles (2015) developed a multiclass four-step model and used a generalized cost function of travel time, monetary fees, and fuel consumption to assess the impact of AV ownership on trip, mode, and route choice behaviors. Three modes of transportation including car, transit, and AV are considered via a nested logit model. AV users were assumed to have the option of either parking the vehicle (with a parking fee) or sending it back to the origin (with no parking fee and incurring fuel costs). Static link performance functions were modified to predict capacity improvements due to AVs on each link. Travelers seek to minimize a generalized cost of travel time, fuel, and parking fees. It is assumed that market penetration, trip productions and attractions are known. The proposed model was tested on the Austin downtown network considering bus routes. Results revealed that parking cost was a main incentive for transit use, and the presence of AV round-trip caused a reduction in transit demand. They predicted a 61.4% reduction in transit ridership as a result of lower costs of AVs.

Hörl (2016) used an agent-based transport simulation model, MATSim, to simulate AVs. Four modes of transportation including public transport, private car, autonomous taxi, and walking are considered in this study. Individuals select their transportation modes such that travel disutility is minimized. Travel disutility for each mode is defined as a function of mode-specific disutility, travel time, and travel cost. The city of Sioux Falls in South Dakota was selected as a test case for the proposed model. Results revealed that the AV mode mainly decreased the share of public transport and walking, meanwhile, it also enabled the shifts of previously private vehicle users. The presence of AVs reduced the average travel distance for public transport and walking agents because long trips in these modes will be replaced by AVs. Moreover, AVs were found to increase VMT which has negative effects on both the environment and congestion. They concluded that the availability of AVs without administrative regulation will attract mode shifts from all the other three modes (i.e. public transport, walking and private car), and will attract more public transport users than private car users.

Zhang et al. (2015) applied an agent-based model to explore potential benefits of SAVs with Dynamic Ride Sharing (DRS). Vehicle trips were generated based on the 2009 National Household Travel Survey (NHTS) data for an imaginary 10-mile by 10-mile grid-based city. They assumed that two individuals may share their ride voluntarily if both of them are willing to share rides with strangers and the higher delay due to ridesharing can be offset by travel cost reductions. They reported that SAV with DRS can provide a better level of service compared to SAV without DRS by reducing trip delay and costs, providing more reliable service particularly in peak hours, and generating less VMT.

The model results indicated that the average delay per trip is approximately 13% lower throughout the day with the presence of SAV with DRS, and around 37% lower during peak hours. Moreover, availability of SAV with DRS was found to generate 4.74% less VMT compared to SAV without DRS.

Childress et al. (2015) assessed the potential change in travel patterns in the Puget Sound region in the state of Washington using an activity-based model. They modeled AV under assumptions of four different scenarios. The first scenario assumes that AVs use existing facilities more efficiently and increase all freeway and major arterial capacities by 30%. The second scenario is built on the first scenario assuming that along with capacity improvements, travelers using AVs will perceive in-vehicle time less burdensome compared to driving in regular vehicles. In the third scenario it is assumed that all cars are self-driving and none are shared. Similar to the third scenario, all cars are assumed to be automated in the final scenario but the main difference is the consideration of SAVs. **Table 2.1** summarizes assumptions used in these four scenarios. To investigate potential effects of AVs, the model outputs from scenario 1 through scenario 4 were compared with the 2010 baseline. Scenarios with a capacity increase (scenarios 1 through 3) experienced increased VMT, ranging from about 4% to 20%.

Table 2.1 Assumptions for the Four Scenarios in Childress et al. (2015)

Assumptions	Scenario 1	Scenario 2	Scenario 3	Scenario 4
1	30% capacity increase on freeways and major arterials	30% capacity increase on freeways and major arterials	30% capacity increase on freeways and major arterials	All trips are provided by AV/SAV
2		The value of time was reduced from \$24 to \$15.6/h for the highest income households	The value of time was reduced from \$24 to \$15.6/h for all households	System provides the same service as private cars but at a higher rate (\$1.65/mi)
3			50% parking cost reduction	

Fagnant et al. (2015) investigated the potential implications of AVs at a low market penetration (1.3% of regional trips). They used an agent-based model to simulate SAVs in a dense urban area of Austin, Texas. Results indicated that each SAV can replace 9 private vehicles, but it increases VMT by 8% due to repositioning trips. In another study, Fagnant and Kockelman (2018), advanced an existing model by enabling DRS, optimizing fleet size, and anticipating profitability for private operators. They showed that availability of SAVs with DRS can limit the VMT increase to 4.5%. Increased market penetration resulted in greater VMT reduction compared to non-SAV fleet. Moreover, they reported that DRS may significantly reduce waiting time, particularly during peak hours.

Figure 2.1 illustrates different ranges of VMT increase estimated by previous studies. Many of these studies are reviewed above (Childress et al., 2015; Fagnant et al., 2015; Fagnant and Kockelman, 2018; Zhang et al., 2015).

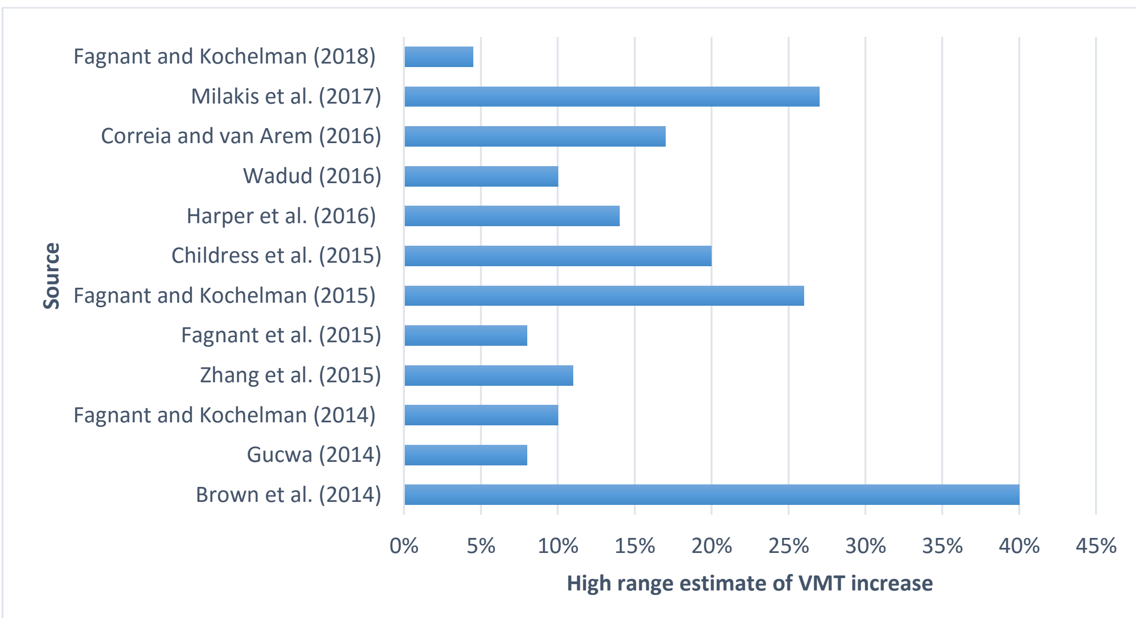

Figure 2.1 Ranges of VMT Increase Estimated by Previous Studies

Several studies explored the number of vehicles that each SAV could potentially replace. **Figure 2.2** summarizes findings of these studies. Bischoff and Maciejewski used an agent-based model to assess the impact of ATs on traffic conditions in Berlin, Germany. Results revealed that one AT could satisfy the demand served by ten conventional taxis.

For Lisbon, Martinez (2015) reported that each SAV with DRS could replace ten private vehicles while SAVs without DRS could only replace six private vehicles. For Singapore, Spieser et al. (2014) suggested that SAVs could meet the mobility needs of the entire population with a fleet size of 1/3 of the conventional passenger vehicles. In another study for Ann Harbor, Michigan, a fleet reduction to 15% was estimated with the presence of SAVs.

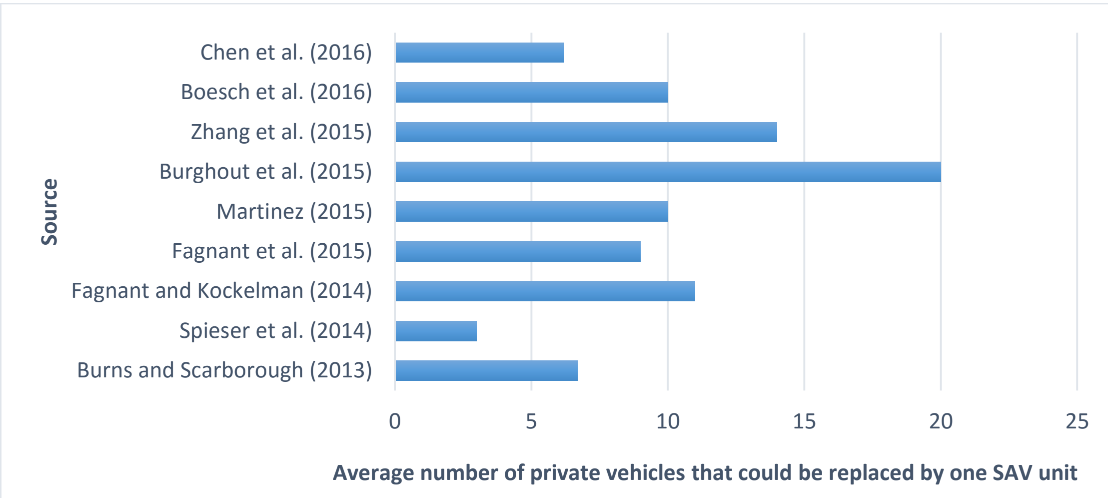

Figure 2.2 Estimated Number of Private Vehicles That Could be Replaced by Each SAV

Availability of SAVs might gradually replace public transport due to its flexibility, convenience, and lower costs. A few studies investigated the impact of AVs and shared mobility services on modal shifts from conventional public transport to vehicle use. For example, Shaheen et al. (2015) analyzed the impact of on-demand ride services on trip mode choice with a survey of 380 TNC users in San Francisco, California. Results indicated that if ridesourcing was unavailable, 39% of TNC users would have taken a taxi, 33% would have taken a bus or rail, and 8% would have walked.

Malokin et al. (2015) investigated the impact of travel-based multitasking on mode choice. They developed a revealed preference Multinomial Logit (MNL) Model based on a survey of 2,120 Northern California commuters to predict mode choice as a function of modal characteristics, socio-economic factors, individual attitudes, and activities conducted during commuting. Results revealed that availability of AVs could result in up to 1% modal shift, mainly from local public transport (bus, light rail, subway), bicyclists, and shared-ride and drive-alone modes.

In another study, Hörl (2016) reported that the presence of AVs could attract 14%, 44%, and 56% shares of car, public transport, and walking modes, respectively (see **Figure 2.3**). Clewlow and Mishra (2017) assessed the impact of ride-hailing services (carsharing and ridesharing services) on travel behavior using a survey deployed in seven major U.S. cities. They found that the presence of on-demand mobility service could decrease shares of public bus, light rail, and bike by 6%, 3%, and 2%, respectively (see **Figure 2.4**). Shen et al. (2017) studied the role of AVs in the public transportation system and proposed a possibility to integrate SAV as a complementary feeder service in the public transit system for solving the last-mile problem. They reported that increasing AV fleet size resulted in higher vehicle kilometers traveled (VKT).

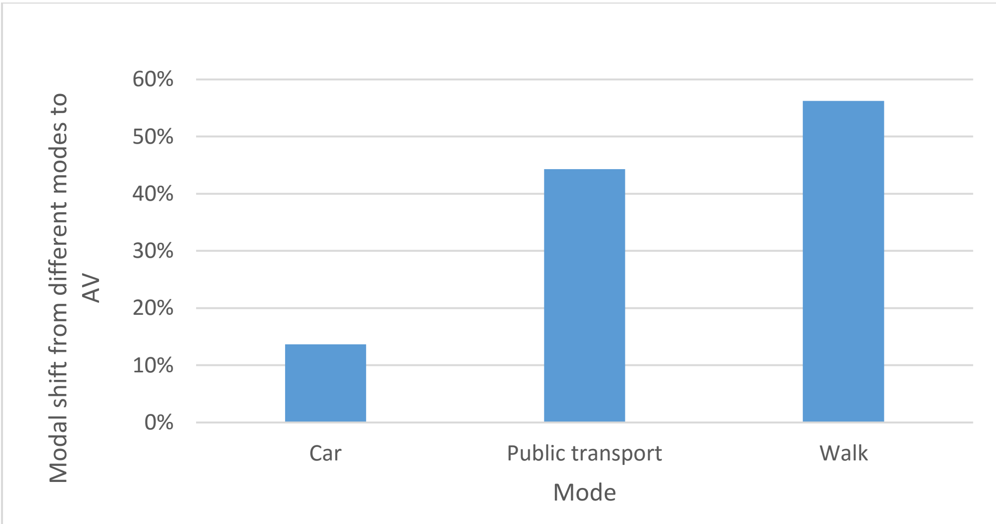

Figure 2.3 Percentage of Modal Shift from Different Transportation Modes to AV (Hörl, 2016)

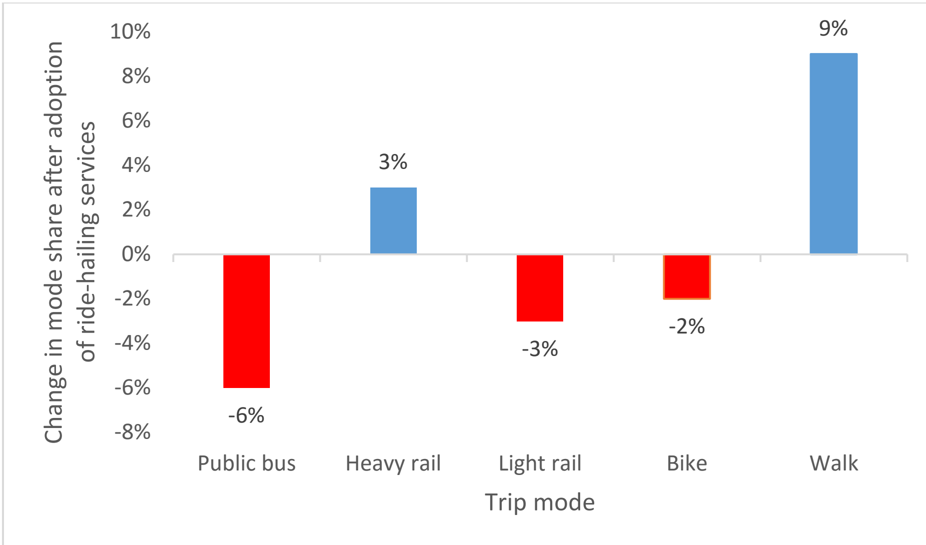

Figure 2.4 Changes in Mode Shares after Adoption of Ride-Hailing Services (Mishra, 2017)

2.3 Impacts of SAVs on Underserved Populations

Many seniors (over the age of 65), people with disabilities or medical conditions, and children, often encounter challenges traveling independently and must rely on family members, friends, government services, and other service providers to meet their mobility needs. For example, Sweeney (2004) reported that on average the disabled population leaves home less often (4.8 days per week) than the non-disabled population (6.1 days per week). AVs present a unique opportunity for these mobility-impaired populations to travel freely and independently, reducing travel disutility. By providing a new mobility option, AVs can lead to increased trip making and increased VMT from seniors, children, and populations with mobility impairments (Anderson et al., 2014).

Based on the Current Population Survey (CPS), there were about 34.2 million people in the U.S. age 65 and older in 2003 (U.S. Census Bureau, 2003). The population of seniors had increased to almost 43.3 million (about a 27% increase) in 2013 and is expected to continue growing in both absolute terms and relative to the rest of the population (U.S. Census Bureau, 2003 and 2013). In 2030, it is projected that roughly 74 million seniors will be living in the U.S., which represents almost 26% of the total U.S. population (Rosenbloom and Winsten-Bartlett, 2002). An increase in seniors' travel demands in the future will create a challenge to transportation systems in providing reliable and efficient service. This highlights the importance of studies to provide insight on the potential future increases in total travel demand from these underserved populations under the influence of vehicle automation.

Several studies attempted to predict the magnitude of the potential future increase in total travel demand from underserved populations made possible by AV technology. For instance, Harper et al. (2016) estimated bounds on the impact of AVs on VMT by the current U.S. population (age 19 and older) under the scenario of increased demand from currently underserved populations (see **Figure 2.1**). The study only focused on changes in travel behaviors of the elderly, non-driving populations, and those with a travel-restrictive medical condition, while AVs could also increase travel of working age drivers (ages 19-64) without medical conditions by increasing the ease of travel. They used the 2009 NHTS which describes travel characteristics of the U.S. population (USDOT, 2011). In order to estimate an upper bound for VMT from underserved populations due to the presence of AVs, three demand wedges with distinct travel behaviors were developed. It is assumed that with the advent of AVs, each person within these populations will increase their annual VMT to a threshold similar to that of a younger or comparable population group (e.g., drivers with no medical restrictions) that currently drives more. They showed that if all three demand wedges were assumed to occur simultaneously, total annual light-duty (car, van, SUV, pickup truck) VMT by the U.S. population (age 19 and older) would increase by 14% or 295 billion miles. Non-drivers were found to have the most contribution to VMT increase by 194 billion miles (9%) while elderly drivers and those with medical conditions increased VMT by 46 billion miles (2.2%) and 55 million miles (2.6%), respectively.

Wadud et al. (2016) estimated an upper bound increase in travel due to new demand from the underserved population. Using NHTS, they showed that the 35-55 age group is the group with the largest fraction of drivers. To address the improved mobility due to AV, they assumed that AV results in the identical share of drivers across all age groups. They also used the data from NHTS and showed that VMT per driver peaks at age 44, then reduces steadily through age 62, and more steeply declines above the age of 62. The steady decline between ages 44 and 62 is assumed to represent a natural rate of decline in travel needs while the sharp decline is assumed to represent reduced travel from impaired driving ability. To capture the impact of AVs they assumed that drivers above 62 will travel as much as drivers of 62 years old. Results revealed that annual VMT could rise up to 10% from increased travel demand due to new users.

Brown et al. (2014) attempted to quantify the impact of automation on energy consumption using the 2009 NHTS and the 2003 “Freedom of Travel” study. They considered the increased travel demand from currently underserved groups and from demand induced by reduced congestion and higher travel speed. Due to increased safety of AVs and also more efficient use of roadway capacity, faster speed and reduced congestion are assumed. Correspondingly, they assumed that VMT increases so as to maintain total time spent traveling. To capture travel demand from underserved populations, they assumed that population segments from age 16 to 85 would begin to travel as the top decile. Results revealed that automation could increase VMT as much as 40%.

2.4 Related Demographic Trends for the Wasatch Front Area

According to Utah’s long-term demographic and economic projections conducted by Kem C. Gardner Policy Institute (Gardner Policy Institute, 2018), the trends of youth and elderly population in the Wasatch Front are shown in **Figure 2.5**. It is observed that from years 2018 to 2065, the elderly population in the Wasatch Front will increase from 396,646 to 1,231,401 (a 210% increase), and the youth population will also increase from 1,066,384 to 1,223,716 (a 15% increase).

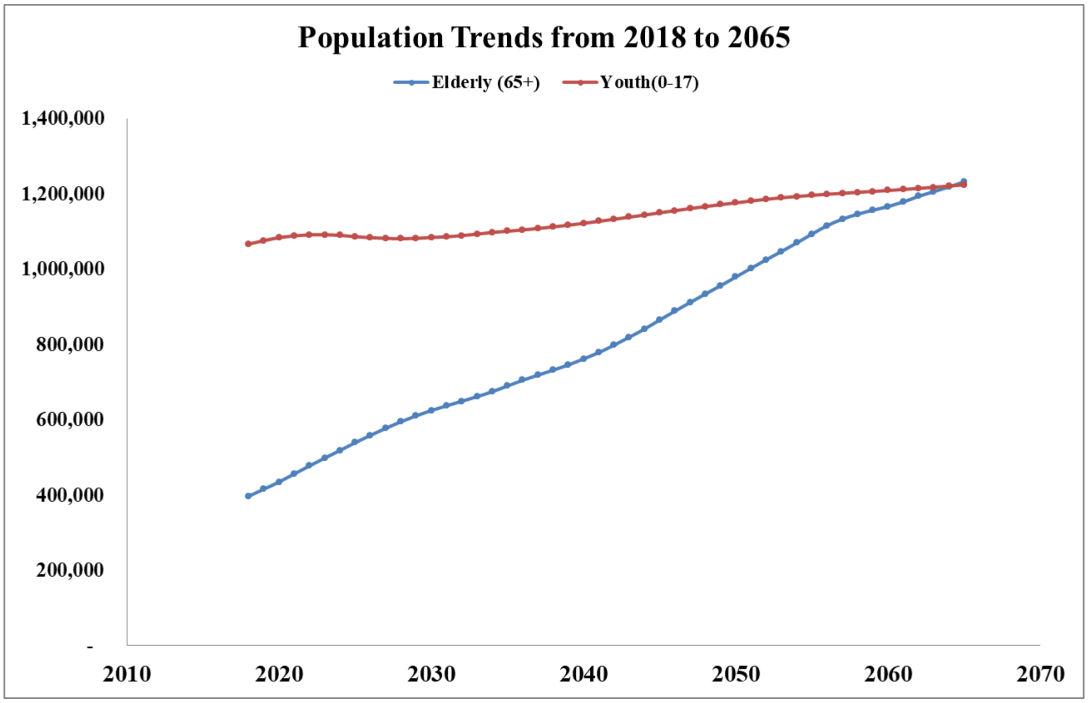

Figure 2.5 Population Projection for the Wasatch Front Area

American Community Survey (ACS) compiles continuous demographic and socio-economic data based on questionnaires sent by mail to over 3.5 million households across the country annually (Wei et al., 2017). The survey estimates the disabled population by disability type and by age group for each census tract within Utah. **Figure *2.6*** illustrates the distribution of Utah disabled population by census tract based on 2012-2016 ACS data.

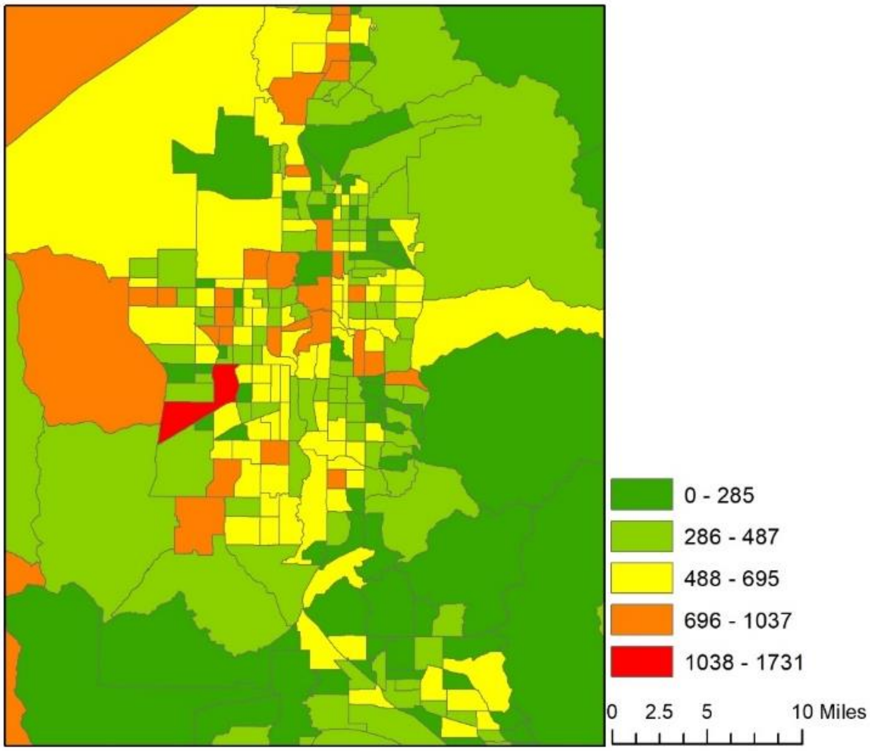

Figure 2.6 Distribution of Utah Disabled Population by Census Tract

2.5 Market Acceptance of SAVs

A myriad of studies has used online surveys to assess public opinion and perception towards AVs. Bansal et al. (2016) investigated public opinions on smart-car technologies using an internet-based survey of 347 adult residents of Austin, Texas. Results indicated that average Willingness to Pay (WTP) for adding Level 4 automation ($7,253) is much higher than that of adding Level 3 automation ($3,300) to conventional vehicles. Individuals who travel more (higher VMT) and those living farther from their workplace exhibited higher WTP for Level 4 compared to Level 3 automation. Elderly people were found to have significantly lower WTP for AVs due to unfamiliarity with new technologies.

They reported that more than 80% of the population appears unwilling to pay more for an SAV service than what current carsharing and ridesharing companies are charging. For trips with short duration during the day, 51% of respondents stated that they are comfortable with sharing a ride with a stranger. Schoettle and Sivak (2015) conducted a web-based survey to understand public opinions regarding various levels of vehicle automation. The survey targeted drivers 18 years and older in the U.S. Results indicated that respondents most frequently preferred no self-driving (45.8%) compared to partially self-driving (38.7%) and completely self-driving (15.5%). Preference for having vehicle automation was found to decrease as respondent age increases. While 45.2% of elderly respondents (60 years and older) were very concerned about riding in a fully self-driving car, only 26.1% of younger respondents (18-29 years old) were very concerned. Females also exhibited greater concern about riding fully self-driving vehicles than men. Piao et al. (2016) used an online survey supplemented with several telephone interviews in La Rochelle to explore user acceptance of ride-sharing AVs. A sample of respondents 18-65 years old was asked to compare automated buses, cars, and taxis with conventional versions of these vehicles. They reported that the majority of the population was positive about automated vehicles if they could offer cheaper service, more space, and more frequent service. Safety and security were two major concerns regarding automated vehicle use, particularly at night. Krueger et al. (2016) conducted a stated preference survey and used a mixed logit model to explore critical determinants of SAV use and the acceptance of dynamic ridesharing (DRS). They surveyed 435 residents in major metropolitan areas in Australia. Results revealed that service attributes including travel time, waiting time, and fares are crucial determinants for SAV usage and DRS acceptance, and younger travelers are more likely to choose SAVs with DRS. Moreover, it was found that current carsharing users are more likely to use SAVs with DRS. While respondents who traveled by car as the driver on the reference trip (i.e. a trip recently made by the respondent) are more likely to use SAVs without DRS, those who traveled by car as a passenger on the reference trip are more likely to use SAVs with DRS. Travelers who exclusively rely on a private car might be reluctant to use an SAV while multi-modal travelers are more likely to adopt SAVs to facilitate their multimodality.

Abraham et al. (2016) conducted an online survey in the U.S. to investigate satisfaction with current in-vehicle technology and inclination to use various levels of automation. Results exhibited that older adults (75 years and older) are less likely to use new mobility solutions such as carsharing (3.9%) and ridesharing (16.2%). They found that younger adults are generally more comfortable with fully automated cars compared to older adults. While 40% of participants aged 25 to 34 selected full automation as the maximum level of automation they would be comfortable with, only 12.7% of participants aged 75 and more chose the same level.

Kyriakidis et al. (2015) conducted a web-based survey with 5,000 respondents from 109 countries to explore user acceptance and willingness to use various levels of automation. Results indicated that most respondents found manual driving as the most enjoyable mode. Respondents were willing to pay more for full automation than partial automation. Of all respondents, 22% stated that they were willing to pay nothing ($0) for full automation, while 5% indicated they would be willing to pay more than $30,000 for full automation.

All of these studies are based on conventional research approaches such as surveys. However, since AVs have not been commercialized yet, respondents do not have real world and concrete experiences with them and may under- or over-value such new technology. This can significantly limit the validity of the results.

As mentioned in previous sections, AVs could have positive impacts on safety, mobility, accessibility, congestion, and the environment. Successful implementation of AV technologies requires public acceptance and adoption over time (Heide and Henning, 2006). There are various contributing factors to AV adoption including both demand-side factors (e.g., willingness to pay) and supply-side factors (e.g., price, infrastructure). Several studies attempted to predict future adoption rates of AV technology. **Figure 2.7** summarizes the findings of these studies.

Bansal and Kochelman (2017) considered various demand-side factors, such as willingness to pay (WTP), vehicle transition decisions, and government regulations on vehicle production along with supply-side factors, such as costs, and technological updates over time. They developed a simulation-based framework to forecast long-term (i.e. year 2045) adoption levels of AV technologies under eight different scenarios based on 5% and 10% annual drops in technology price, 0%, 5%, and 10% annual increments in WTP; and changes in government regulation (e.g., mandatory connected vehicle technology). Results revealed that under various assumptions, Level 4 AVs are likely to be adopted by 24.8-87.2% of the vehicle fleet in 2045. Lavasani et al. (2016) developed a market penetration model for AV technology adoption based on similar technology adoption in the past. They incorporated AV price and economic wealth into the models. Results showed that AV adoption increases to 79% by year 2045 and eventually the market will reach saturation in 2059.

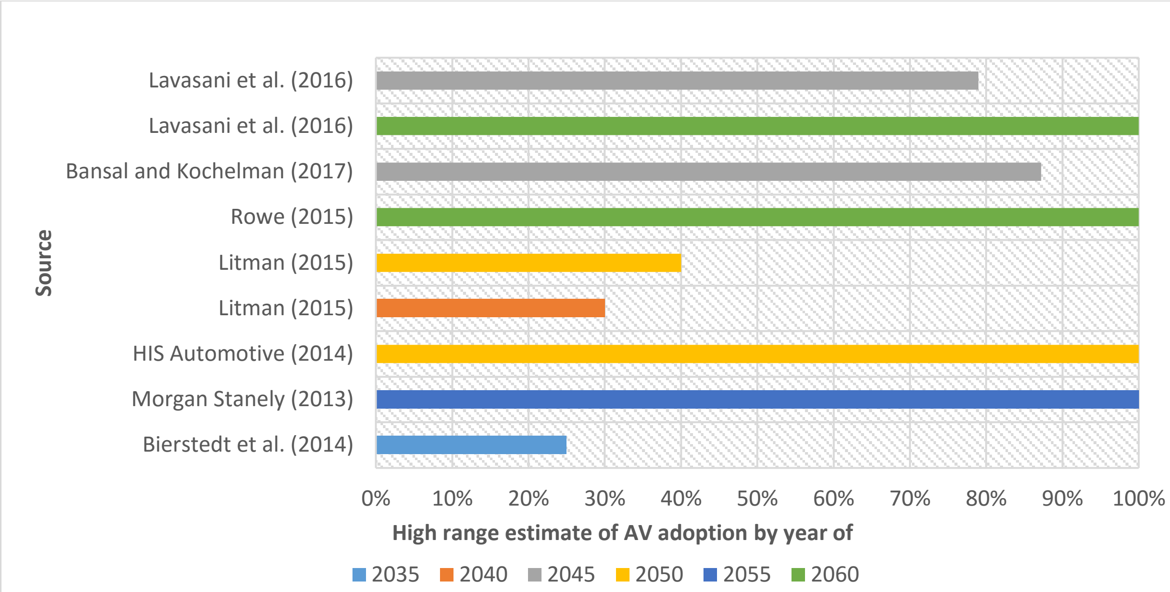

Figure 2.7 Future Adoption Rates of AV Technology

2.6 Availability of SAVs by Land-Use Type (Urban, Suburban, Rural)

Although most studies on SAVs focused on the applications in urban areas, some researchers considered the performance of SAVs in suburban or rural areas where trips have different features than urban trips, e.g., long travel distance, with absence of public transit, and/or long wait time (Bösch et al., 2017; Burns et al., 2013; Chen and Kockelman, 2016; Lavieri et al., 2017; Liu et al., 2017; Meyer et al., 2017). **Table 2.2** provides a summary of the land-use type that each study touched upon as well as the topic of interest.

Table 2.2 Summary of Land-Use Type Studies and Topic of Interest

Study	Land-use type	Topic of interest
(Burns et al., 2013)	Small urban and suburban; small to medium city; large urban area	Travel costs
(Bösch et al., 2017)	Urban; suburban and exurban	Costs of personal mobility system
(Lavieri et al., 2017)	High-density living area; low-density living area	Utility of SAV

(Liu et al., 2017)	Urban; suburban; exurban	Transportation pattern with SAV
(Chen and Kockelman, 2016)	Downtown; urban; suburban; exurban	Market potential
(Meyer et al., 2017)	City; countryside	Travel demand and accessibility

Burns et al. (2013) evaluated the performance of a new personal mobility system consisting of SAV fleets in three distinctly different areas: Babcock Ranch, Ann Arbor, and Manhattan. These three areas were selected as being representative of small urban and suburban areas, small to medium cities, and large urban areas with well-developed public transit systems in the U.S. The system performance was quantified as a cost reduction by switching from personal car ownership to the personal mobility system. For each case, they initially obtained the original travel data in the study area, including number of trips, trip duration, trip distance, speed, and number of passengers. Then they conducted a simulation to estimate the number of AVs to provide the same coverage with a reasonable wait time. Once the fleet sizes became known, they estimated the costs of owning and operating the autonomous fleets and compared with the costs of personal car ownership. They found that the personal mobility system can effectively reduce travel costs compared with personal car ownership: in small urban and suburban areas, the cost would be $4 per day per person, or under $2 per trip on average; in small to medium-sized cities, the travel cost is reduced from $1.6 per mile to $0.15 per mile; and in large urban areas with well-developed public transit systems, the cost is reduced from $4 per mile by taxi to $0.50 per mile. Besides the cost savings, they found that the fleets result in great efficiency and convenience.

Bösch et al. (2017) aimed to identify a suitable operational model for SAVs in urban and regional settings (suburban and exurban), by comparing the costs of such service with traditional public transit. A series of assumptions in terms of costs and cost structures have been made in estimating the costs of SAV service, private car, and public transit. They assumed several cost changes related to SAVs. For example, SAVs can reduce driver labor costs but increase maintenance costs, especially cleaning costs, since the passengers may be more irresponsible in the vehicle in the absence of a driver. Vehicle automation will increase the purchase price but decrease insurance costs since SAVs provide safer driving than human drivers. By comparing the costs in urban and regional settings, they found that public transit will still be economically competitive in dense urban areas, where it can be offered at lower prices. In the areas where demands cannot be bundled, SAVs will be more efficient. But whether SAV is the most efficient alternative still depends on the costs of purchase, operation, and maintenance.

Liu et al. (2017) conducted a large-scale micro-simulation of transportation patterns in a metropolitan area and its vicinity when relying on a system of SAVs. Multiple fare levels of SAVs have been tested in the simulation. They found that with the increase of the SAV fare rate, SAVs are less likely to be chosen, especially in rural areas where trips are likely to be longer. For lower SAV fare rates ($0.5 or $0.75 per mile), SAVs are preferred in rural areas over human-driven vehicles, but for higher fare rates ($1.0 or $1.25 per mile), SAVs are more favorable in urban areas. Chen and Kockelman (2016) explored the market potential of shared autonomous electric vehicles (SAEV) with a multinomial logit mode choice model in a hypothetical domain with four zones: downtown, urban, suburban, and exurban. In their model, SAEV competes with privately-owned AVs, human-driven vehicles, and city buses. SAEV speed, parking fee, and transit access and wait time in the utility functions vary by zone. They also designed four pricing schemes for SAEV: distance-based, origin-based, destination-based, and a combination of origin and destination. Their results showed that SAEVs replace former short transit trips between zones, especially in suburban and exurban zones, due to shorter wait times. In Meyer et al. (2017), they modeled the travel demand and estimated the accessibility in Switzerland when private vehicle ownership has been fully replaced by SAVs. They found that the increase in demand varies from 0 in some rural areas to 180% in Zurich city center. Another finding was that in 85% of the region, the accessibility is improved, but the remaining 15% - mostly cities - suffers accessibility losses. When weighted by population, the national average accessibility only increases by 1.4%, meaning that the accessibility losses in cities offset the gains in the countryside.

In summary, this literature review supports the following approach to investigating the question of how SAVs would affect VMT in Utah:

1) A four-step travel model is a useful tool for exploring this question. For this research, the WF Travel Demand Model is an appropriate analytical tool.

2) The trip generation module of the WF Travel Model enables an analysis of increased mobility for households with youth and elderly members, and people with travel-restrictive medical conditions.
3) A fully evolved "Shared Autonomous Vehicle" represents a new mode of travel – Mobility as a Service (MaaS) -- that has lower or competitive operating costs when compared to other modes for similar trips.
4) The competitiveness of MaaS to other modes will depend on travel time and cost competitiveness which, in turn, are somewhat dependent on the land-use types served by each mode.
5) The WF Travel Model can be used as a scenario evaluation tool, where low, medium, and high impacts along both the trip generation and mode share dimensions can be explored.

3. RESEARCH METHODS

3.1 Overview

In order to estimate the range of VMT changes due to SAVs, the current version of WF travel demand model is modified to represent low-, medium-, and high-impact scenarios. These model modifications were made mainly on trip generation and mode choice modules. The following sections describe WF travel demand model and modifications made to WF trip generation and mode choice modules in order to accommodate SAVs in the current version of the model.

3.2 WF Travel Model

In order to capture the impact of SAVs on VMT, we modified the WF travel demand model, which is maintained jointly by WFRC and MAG. It is a trip-based travel model that estimates the movement of people and vehicles within the 4-County (Weber, Davis, Salt Lake, and Utah) urbanized area during an average spring/fall weekday.

The research used model version 8.2. The model includes auto, transit, and non-motorized modes. Transit is comprised of bus, BRT, light rail, and commuter rail. The model is a zone-based forecasting tool, modeling travel between land uses aggregated into Transportation Analysis Zones (TAZs). There are 2,263 TAZs including 20 external TAZs in the model. **Figure 3.1** shows model TAZ structure.

The socioeconomic data and developable acres in a TAZ are used to calculate the urbanization value for each TAZ. The urbanization value is calculated as follows:

$$Urbanization = (POP_{eightzone} + 2.07 * EMP_{eightzone})/DEVACRES_{eightzone} \quad (3\text{-}1)$$

Where $POP_{eightzone}$ denotes the total population of one zone plus four closest neighbor zones, $EMP_{eightzone}$ is the total employment of one zone plus four neighbor zones, and $DEVACRES_{eightzone}$ is the total developable acres of one zone plus four neighbor zones.

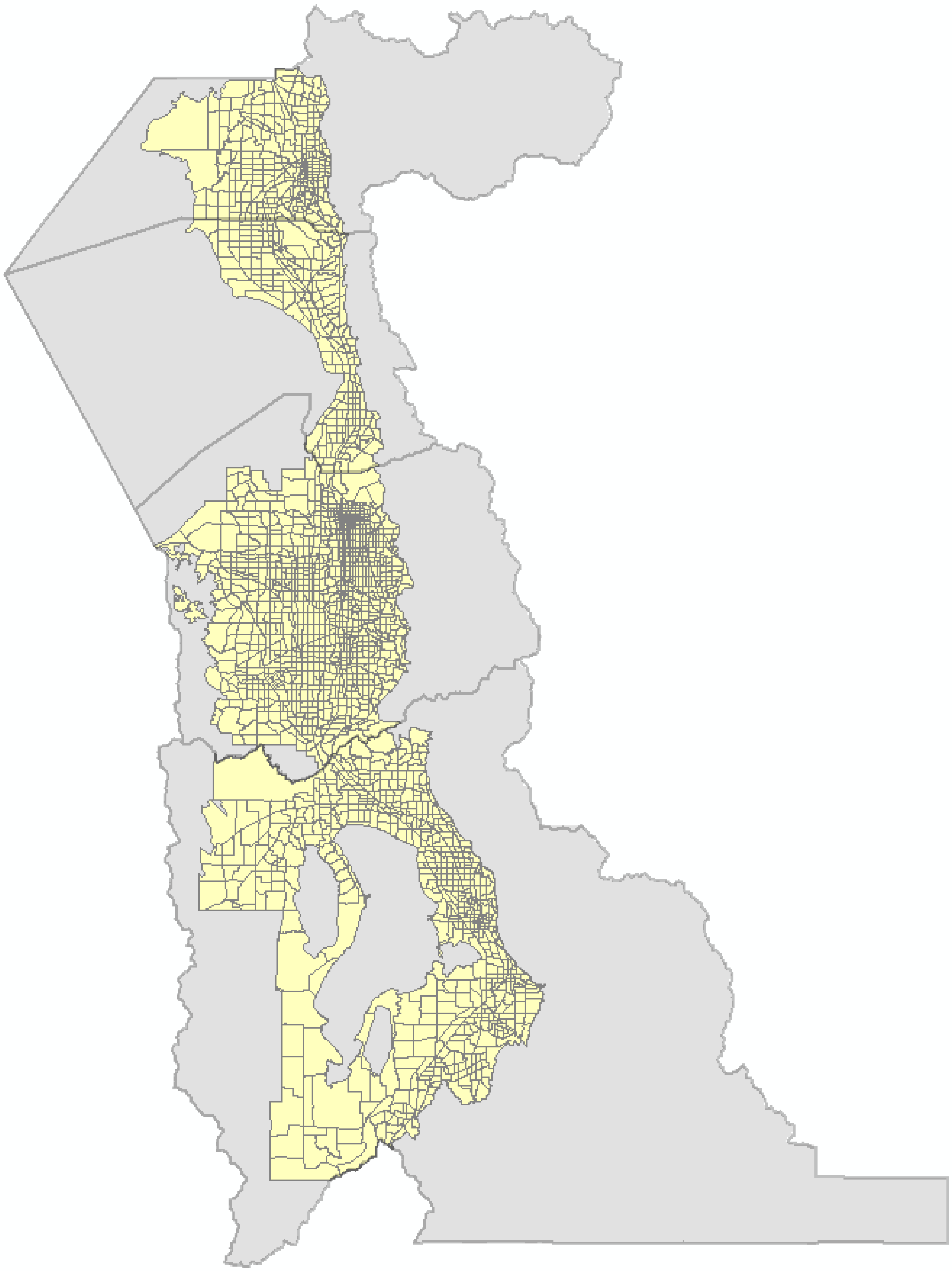

Figure 3.1 WFRC/MAG Travel Model TAZ Structure (yellow represents WFRC/MAG TAZs)

The urbanization value is used to categorize the TAZs into one of the five area types, shown in **Table 3.1**. TAZs area types for years 2011 and 2040 are determined based on urbanization values visualized in **Figure *3.2***.

Table 3.1 Urbanization Threshold Used to Determine TAZ Area Type

Urbanization	Area Type
0 - 1	Rural
1 - 5	Transition
5 - 15	Suburban
15 - 45	Urban
> 45	CBD

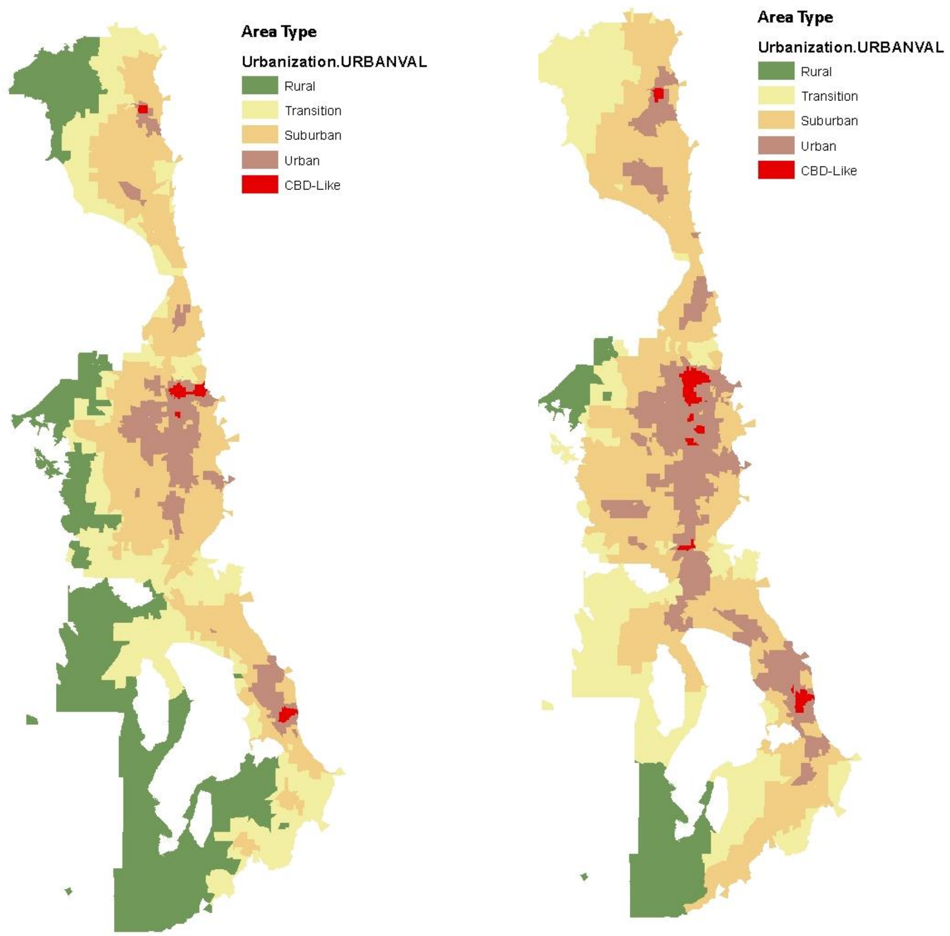

Figure 3.2 Area Types for Years 2011 and 2040

The road network in the model includes facilities functionally designated as collector or above by UDOT and some local roads in the 2011 base year. There are approximately 27,000 road links in the base year network. The transit network in the model includes all Utah Transit Authority (UTA) bus and rail routes, excluding ski routes, vanpools, and commuter buses to specific employers. The transit network distinguishes local buses, enhanced buses, express buses, BRT, light rail, and commuter rail. Future year 2040 roadway and transit networks are developed for the model consistent with the regional transportation plan.

The WF travel demand model is a classic four-step model consisting of four sub-models:

- trip generation;
- trip distribution;
- mode split; and
- trip assignment.

Figure 3.3 shows the conceptual overview of the WF model. The model has a feedback loop between trip distribution and traffic assignment which ensures consistency between congestion and travel times that influence trip distribution patterns. The trip generation model first estimates trip-ends by TAZ based on household and employment characteristics. Households are stratified jointly by life cycle, income, household size, and number of workers. Three different life cycle categories are considered in the model as follows:

- LC1: Households with no children and no seniors
- LC2: Households with children and no seniors
- LC3: Households with seniors (may have children)

The trip distribution model then pairs generated trip-ends into trips. In the mode choice model, a mode of travel is identified for each trip. Vehicle trips are assigned to the highway network in the trip assignment model, during which congestion levels on each road are estimated consistent with route choices. Transit trips are assigned to the transit network in the mode choice step.

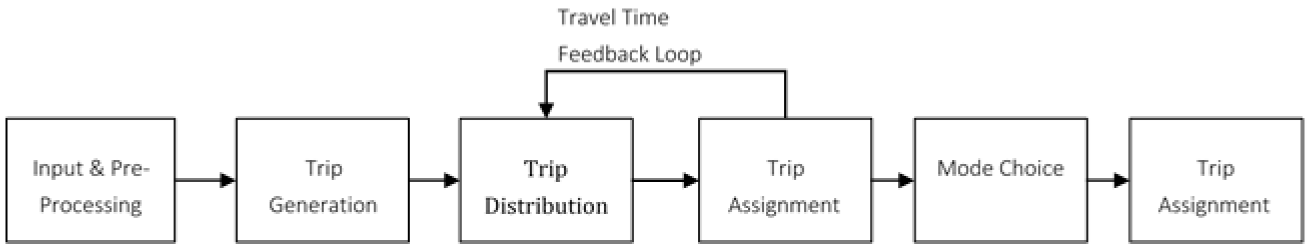

Figure 3.3: Conceptual Overview of the WFRC/MAG Travel Model

The trip generation and trip distribution models are daily models, while the mode choice model distinguishes peak and off-peak periods. The traffic assignment model estimates traffic flow for four periods of the day:

- AM Peak: 6 - 9 AM
- Midday: 9 AM – 3 PM
- PM Peak: 3 – 6 PM
- Evening/Off-Peak: 6 PM – 6 AM

The model includes several trip purposes. Trip purposes are grouped into three main classifications: person trips, commercial vehicle/truck trips, and external vehicle trips. Person trips are further categorized by different trip purposes, as follows:

- **Home-Based Work Trips (HBW)**: Trips made between the traveler's home and the place of work, in either direction.
- **Home-Based College Trips (HBC)**: Trips made between the traveler's home and college.
- **Home-Based School Trips (HBSch)**: Trips made between the traveler's home and school. HBSch trips include kindergarten through high school.
- **Home-Based Shopping Trips (HBShp)**: Trips made between the traveler's home and shopping (e.g. retail) locations.
- **Home-Based Other Trips (HBOth)**: Trips made between the traveler's home and all other non-work-related destinations not already accounted for by the previously defined trip purposes.
- **Non-Home-Based Work Trips (NHBW)**: Trips made between the traveler's work and some other non-home location.

- **Non-Home-Based Non-Work Trips (NHBNW)**: Trips made between non-home and non-work locations.

The trip generation and distribution models include the most detailed information in terms of trip purposes. After trip distribution, the HBShp and HBOth trip purposes are combined into an HBO category, and NHBW and NHBNW are combined into NHB.

The model is calibrated to represent 2011 base-year travel conditions by adjusting model input data, assumptions and parameters so that intermediate and final outputs could closely match observed data. Model outputs are validated against real-world data. Origin-Destination flows, roadway vehicle volumes, vehicular travel times and speeds, and transit ridership are some of the model outputs used for validation. For future forecast years, the model output is reviewed for "reasonableness" to validate model results.

3.3 Trip Generation Modifications

Previous studies reveal that SAVs can increase the mobility of specific underserved populations. Many seniors, people with travel-restrictive disabilities or medical conditions, and children, often encounter challenges traveling independently and must rely on family members, friends, and other service providers to meet their mobility needs.

In this research we assumed that SAVs will improve the mobility of these populations for non-work and non-school trips. Since work-based and school-based trips are among those necessary trips that every traveler including underserved populations is regularly making, it is not expected that SAVs will affect much the number of these specific trip purposes. SAVs may, however, increase trip making for other, discretionary trips. To address the improved mobility of underserved population, the following modifications are made to the WF demand model:

3.3.1 Impact on households with children and elderly

To capture the improved mobility of children and elderly members in the WF model, we increased the trip rates of households classified under LC2 and LC3 for non-work and non-school trip purposes. It is assumed that before the introduction of SAV, children and elderly members of high-income households have higher mobility than lower income households since they are less constrained by travel costs. Based on this assumption, we can expect that the availability of the SAV mode can provide the same mobility for lower income households. Thus, SAVs will increase trip generation rates for lower income households toward the trip generation rates of higher income households.

The 2012 household travel diary data is used to extract the high-income household trip generation rates by life cycle and household size for three trip purposes: HBO, HBShp, and NHBNW. Once these rates are calculated, the trip rates for different trip generation scenarios are calculated as follows:

$$TR_{LSP_i} = TR_{LSP_{Base\ Model}} + \beta_i * (TR_{LSP_{High\ Scenario}} - TR_{LSP_{Base\ Model}}) \qquad (3\text{-}2)$$

where TR_{LSP_i} and $TR_{LSP_{Base\ Model}}$ denote the trip generation rates for households with life cycle L, size S, and trip purpose P in scenario i and base year scenario, respectively. $TR_{LSP_{High\ Scenario}}$ represents the trip generation rate for households with life cycle L, size S, and trip purpose P for high-income population and β_i is the adjustment factor for scenario i.

When β_i is 1, the trip generation rates for all income categories are set to those of high-income households. When β_i is 0, the trip generation rates for all income categories are set to those of the base model (null or "no build"). Different values for β_i are used to populate three scenarios with different trip generation growth. For low-, medium-, and high-trip generation scenarios, β_i is set to 0.1, 0.5, and 1, respectively.

Figure ***3.4*** shows the trip rates of households under LC2 and LC3 categories for non-work and non-school trip purposes against household size. Grey and yellow plots show the trends of trip rate increase before improving the mobility of LC2 and LC3. The blue and orange plots illustrate the same trends after improving the mobility for LC2 and LC3 households. As shown in this figure, for most households, trip rates increase as the household size increases. Moreover, the trends of the trip-rate increase are consistent before and after the mobility improvement. There are three cases that the trends of trip rate increase after mobility improvement are not consistent with that of before improvement. This might be explained with small sample size of households within these categories in household travel diary data. These trip rates are adjusted to follow the same trend as before mobility improvement (as shown in the second column of graphs in Figure 3.4 titled "After Adjustment")

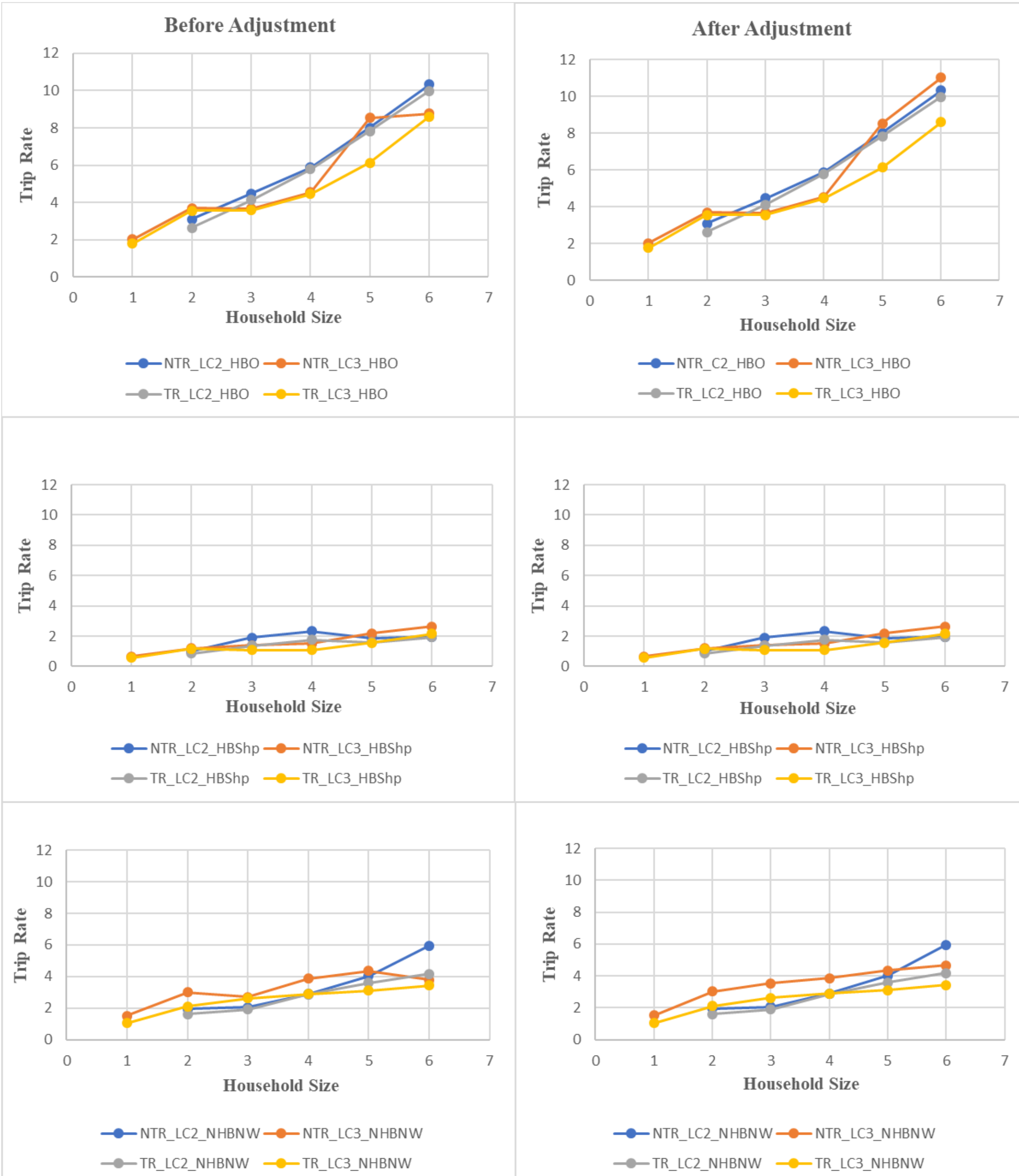

Figure 3.4: Trip Rates Before and After Adjustments (TR: Trip Rate before SAV and NTR: New Trip Rate after SAV, Considering Improved Mobility of Children and Elderly Populations)

3.3.2 Impact on Mobility-Impaired Populations

SAVs can potentially increase the mobility of the mobility-impaired population (i.e. people with driving-restrictive medical conditions) for non-work and non-school trips. Ideally, SAVs would enable a mobility-impaired traveler to generate the same number of trips as a traveler with no impairment. The current WF travel model does not differentiate between people with driving-restrictive medical conditions and those without. Thus, it can be assumed that the current model trip generation rates are weighted average of trip generation rates for disabled and non-disabled population as follows:

$$TR_{base} = TR_{WD} * P_{WD} + TR_{WOD} * P_{WOD} \qquad (3\text{-}3)$$

where TR_{base} denotes trip generation rates in the base model, TR_{WD} and TR_{WOD} represent the trip generation rates of households with and without mobility-impaired members in the study region, and P_{WD} and P_{WOD} are the percentages of households with and without mobility-impaired members in the study region. We assumed a trip reduction (or suppression) rate (TRR) for households with mobility-impaired members and calculated trip rates for those households as follows:

$$TR_{WD} = TR_{WOD} * (1 - TRR) \qquad (3\text{-}4)$$

Based on the finding of Sweeney (2004), the trip suppression rate for households with mobility-impaired members is assumed to be 20%, meaning that households with mobility-impaired members on average generate 20% fewer trips than households without mobility-impaired members.

The percentage of households with mobility-impaired members within the study region is obtained from 2012-2016 ACS which was collected at the census tract level. Finally, the trip generation rates for households without mobility-impaired members are calculated as:

$$TR_{WOD} = \frac{TR_{base}}{(1 - P_{WD}) + ((1 - TRR) * P_{WD})} \qquad (3\text{-}5)$$

To populate scenarios with various trip generation growth rates, TRR is adjusted to smaller values reflecting various levels of mobility improvements for households with mobility-impaired members. When TRR is 20%, the trip generation rates are equal to the base model trip generation rates; when TRR is 0%, households with mobility-impaired members are assumed to generate the same number of trips as households without mobility-impaired members. For this research, 15%, 10%, and 0% TRR are respectively assumed for low-, medium- and high-trip generation scenarios.

Using equation 3-3, trip rates increased due to the improved mobility of households with mobility-impaired members are estimated. This results in trip rate increases of 0.3%, 0.5%, and 1% for low-, medium-, and high-trip generation scenarios, respectively. **Table 3.2** summarizes the modified trip rates and their increase percentage to capture the improved mobility of underserved population in the WF trip generation model.

Table 3.2 Modified Trip Rates for Different Trip Generation Scenarios

HH Size	Life Cycle	Trip Purpose	Base Model Rates	Low Scenario		Medium Scenario		High Scenario	
				Increase Percentage	Trip Rate	Increase Percentage	Trip Rate	Increase Percentage	Trip Rate
1	1	HBOth	1.301	0.30	1.305	0.50	1.308	1.00	1.314
2	1	HBOth	2.322	0.30	2.329	0.50	2.334	1.00	2.345
3	1	HBOth	3.569	0.30	3.580	0.50	3.587	1.00	3.605
4	1	HBOth	5.214	0.30	5.230	0.50	5.240	1.00	5.266
5	1	HBOth	7.265	0.30	7.287	0.50	7.301	1.00	7.338
6	1	HBOth	9.5685	0.30	9.597	0.50	9.616	1.00	9.664
2	2	HBOth	2.634	2.05	2.688	9.26	2.878	18.61	3.124
3	2	HBOth	4.128	1.15	4.175	4.75	4.324	9.54	4.522
4	2	HBOth	5.784	0.47	5.811	1.35	5.862	2.71	5.941
5	2	HBOth	7.826	0.54	7.868	1.71	7.960	3.42	8.094
6	2	HBOth	9.9762	0.64	10.040	2.22	10.198	4.46	10.422
1	3	HBOth	1.785	1.63	1.814	7.15	1.913	14.36	2.041
2	3	HBOth	3.558	0.68	3.582	2.40	3.644	4.83	3.730
3	3	HBOth	3.569	0.57	3.590	1.88	3.636	3.77	3.703
4	3	HBOth	4.461	0.50	4.483	1.48	4.527	2.98	4.594
5	3	HBOth	6.128	4.25	6.388	20.27	7.370	40.74	8.625
6	3	HBOth	8.6	3.11	8.868	14.59	9.855	29.32	11.121
1	1	HBShp	0.452	0.30	0.453	0.50	0.454	1.00	0.457
2	1	HBShp	0.72	0.30	0.722	0.50	0.724	1.00	0.727
3	1	HBShp	0.753	0.30	0.755	0.50	0.757	1.00	0.761

4	1	HBShp	1.075	0.30	1.078	0.50	1.080	1.00	1.086
5	1	HBShp	1.559	0.30	1.564	0.50	1.567	1.00	1.575
6	1	HBShp	2.15	0.30	2.156	0.50	2.161	1.00	2.172
2	2	HBShp	0.86	2.05	0.878	9.26	0.940	18.61	1.020
3	2	HBShp	1.355	4.25	1.413	20.28	1.630	40.75	1.907
4	2	HBShp	1.752	3.66	1.816	17.31	2.055	34.78	2.361
5	2	HBShp	1.58	2.11	1.613	9.56	1.731	19.20	1.883
6	2	HBShp	1.924	0.53	1.934	1.65	1.956	3.31	1.988
1	3	HBShp	0.57	1.92	0.581	8.63	0.619	17.34	0.669
2	3	HBShp	1.161	0.64	1.168	2.22	1.187	4.45	1.213
3	3	HBShp	1.075	3.36	1.111	15.83	1.245	31.81	1.417
4	3	HBShp	1.075	4.35	1.122	20.80	1.299	41.80	1.524
5	3	HBShp	1.559	4.25	1.625	20.27	1.875	40.74	2.194
6	3	HBShp	2.15	2.56	2.205	11.83	2.404	23.78	2.661
1	1	NHBNW	0.892	0.30	0.895	0.50	0.896	1.00	0.901
2	1	NHBNW	1.247	0.30	1.251	0.50	1.253	1.00	1.259
3	1	NHBNW	1.828	0.30	1.833	0.50	1.837	1.00	1.846
4	1	NHBNW	2.15	0.30	2.156	0.50	2.161	1.00	2.172
5	1	NHBNW	2.473	0.30	2.480	0.50	2.485	1.00	2.498
6	1	NHBNW	2.795	0.30	2.803	0.50	2.809	1.00	2.823
2	2	NHBNW	1.613	2.40	1.652	11.03	1.791	22.16	1.970
3	2	NHBNW	1.914	1.10	1.935	4.52	2.001	9.08	2.088
4	2	NHBNW	2.87	0.36	2.880	0.78	2.892	1.57	2.915
5	2	NHBNW	3.591	1.54	3.646	6.69	3.831	13.44	4.074
6	2	NHBNW	4.171	4.61	4.363	22.08	5.092	44.37	6.022
1	3	NHBNW	1.054	4.73	1.104	22.68	1.293	45.58	1.534
2	3	NHBNW	2.118	4.55	2.214	21.77	2.579	43.75	3.045
3	3	NHBNW	2.634	3.71	2.732	17.60	3.098	35.38	3.566
4	3	NHBNW	2.903	3.62	3.008	17.11	3.400	34.39	3.901
5	3	NHBNW	3.118	4.25	3.250	20.27	3.750	40.74	4.388
6	3	NHBNW	3.44	3.88	3.573	18.42	4.074	37.02	4.714

3.4 Mode Choice Modifications

Current WF travel model uses a nested multinomial logit mode choice model to estimate the split among non-motorized (walk/bike) and motorized (auto and transit) trips. **Figure 3.5** illustrates model layout. The mode choice model estimates the modes of travel separately for HBW, HBO, HBC and NHB trips. The mode choice model also evaluates the mode of a trip separately for peak (AM plus PM) and off-peak (MD plus EV) periods. Mode choice model coefficients vary by trip purpose but not by time period. Differences in time-period utilities are handled by the mode-specific constants. For this research, a new mode —MaaS – was created to accommodate SAVs in the current mode choice model. The MaaS mode is added as a new branch within the motorized branch. The layout of the new mode choice model is shown in **Figure 3.6**.

The MaaS utility function is calculated based on in-vehicle time, initial pick-up time, operating cost (i.e. the distance-based cost, time-based cost, and initial fee), cost split factor, and pick-up time factor. **Table 3.3** through **Table 3.6** show the values used for these variables and coefficients across different scenarios. The in-vehicle time is reduced to make travel time less burdensome for MaaS compared to conventional transportation modes. The operating cost of MaaS for the base scenario is based on current Uber and Lyft fares in Salt Lake City, Utah. All rates are in 2010 dollars. For medium- and high- MaaS market-penetration scenarios, operating cost is reduced reflecting a less expensive SAV mode. Variable initial pick-up time based on area type is used for MaaS across all scenarios. The initial pick-up time is the time spent after a passenger is dropped off and prior to the next passenger pickup. It is lower in a Central Business District (CBD) than in Urban and Rural areas due to availability of more MaaS mode. For shared rides, cost split factor is used to split the operating costs between passengers. Moreover, a pick-up time factor is utilized to penalize initial pick-up time for MaaS shared ride modes.

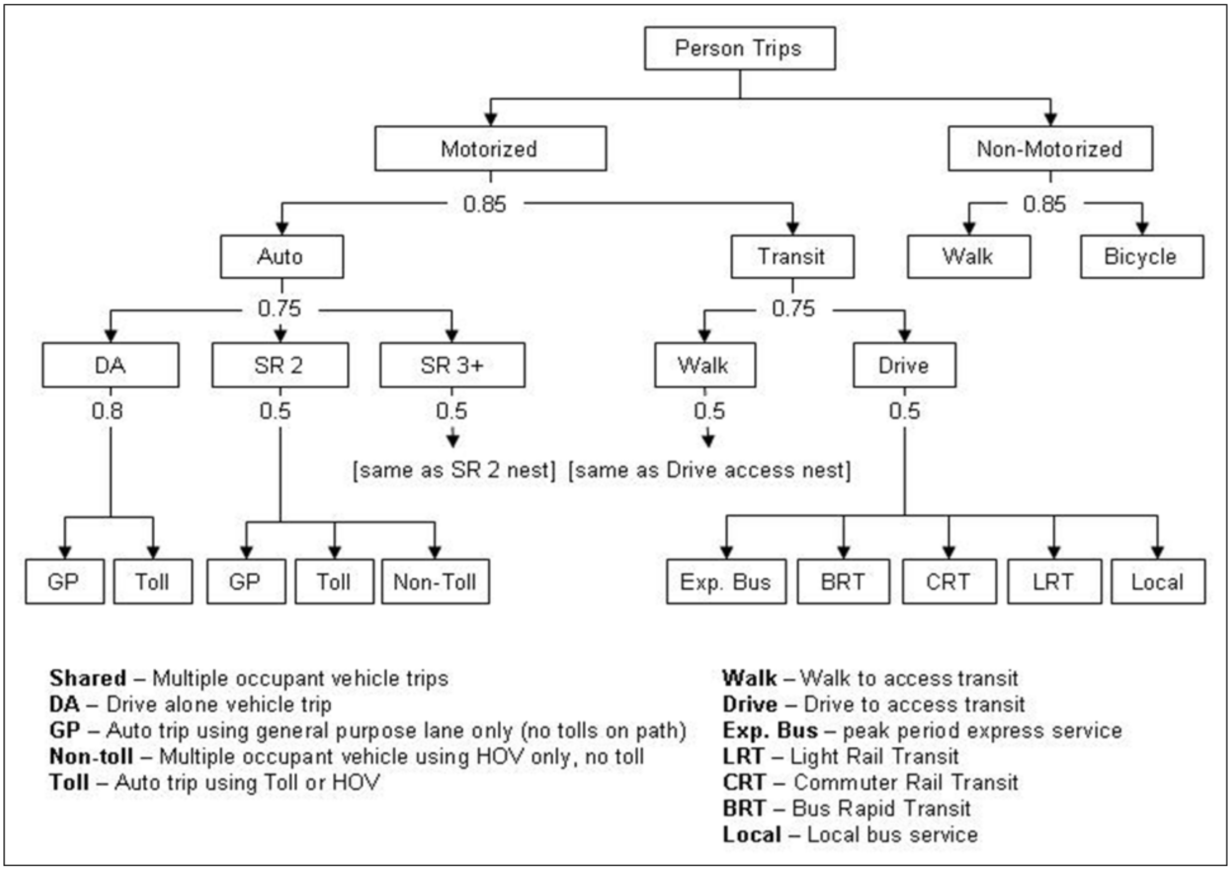

Figure 3.5 Current WF Mode Choice Model

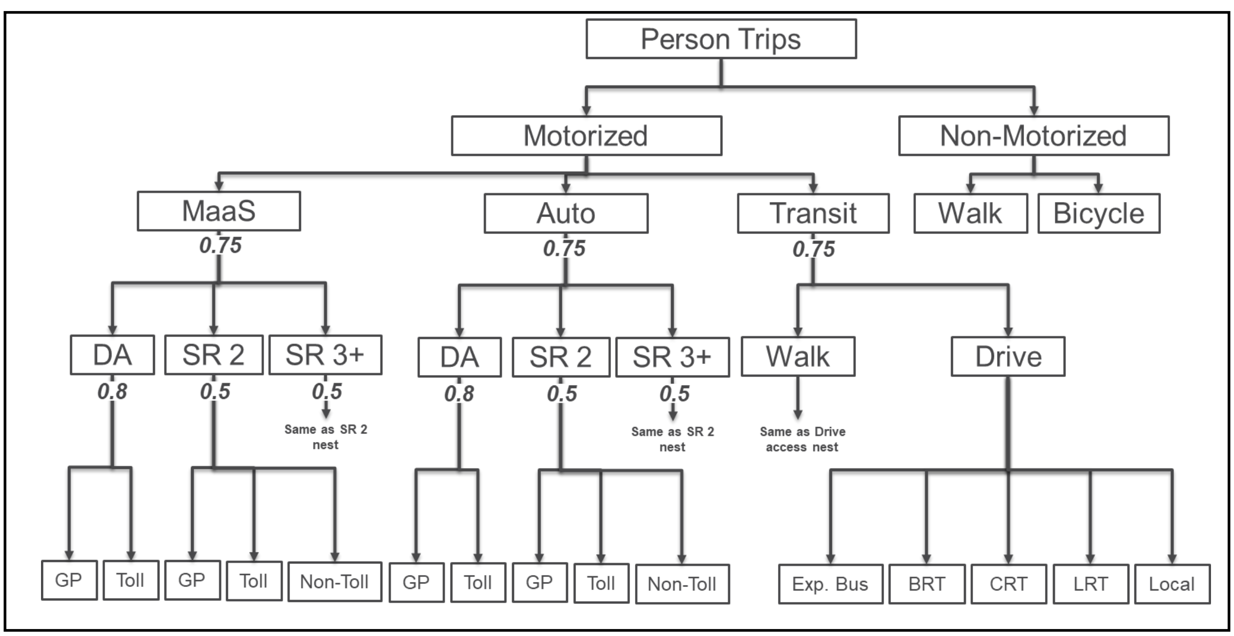

Figure 3.6 Modified WF Mode Choice Model for Accommodating SAVs

Table 3.3 MaaS In-Vehicle Time Values across Different Scenarios

Trip Purpose	In Vehicle Time for Scenario			
	Base	Low	Mid	High
HBW	-0.045	-0.0405	-0.036	-0.0315
HBO	-0.035	-0.0315	-0.028	-0.0245
NHB	-0.04	-0.036	-0.032	-0.028
HBC	-0.025	-0.0225	-0.02	-0.0175

Table 3.4 MaaS Operating Cost across Different Scenarios

Cost Type	Operating Cost for Scenario		
	Low/Base	Mid	High
Distance-Based Cost ($/mile)	0.679	0.611	0.543
Initial Fee ($)	2.590	2.331	2.072
Time-Based Cost ($/min)	0.174	0.157	0.139

Table 3.5 MaaS Initial Pick-up Time in Different Area Types Across Scenarios

Area Type	Scenario		
	Low/Base	Mid	High
CBD Core	3	3	3
CBD	5	5	5
Urban	8	7.2	6.4
Urban-Rural	12	10.8	9.6
Rural	15	13.5	12

Table 3.6 Cost Split Factor and Pick-Up Time Factor for Shared MaaS Modes

Mode	Cost Split Factor	Pickup Time Factor
MaaS 2	0.7	1.5
MaaS 3+	0.6	2

3.5 VMT Estimation

VMT from MaaS vehicle repositioning occurs after a passenger is dropped off and prior to the next passenger pickup. Regarding additional VMT from repositioning trips, the level of aggregation in the four-step model makes it very challenging to accurately model repositioning trips within the current modeling framework. As a result, we conducted an off-model analysis to estimate the additional VMT incurred due to those repositioning trips. The additional VMT for each MaaS trip is estimated based on initial peak/off-peak pick-up time and average speed within the trip origin area type. For shared ride modes additional pick-up time is considered. Equations 3-6 and 3-7 show how additional VMT is estimated for peak period and off-peak period.

$$VMT_{Repos,Pk} = \sum_{i=1}^{5} MaaS_{i,\,Pk} * Speed_{i,Pk} * PickUp_i \tag{3-6}$$

$$VMT_{Repos,Ok} = \sum_{i=1}^{5} MaaS_{i,\,Ok} * Speed_{i,Ok} * PickUp_i \tag{3-7}$$

where $VMT_{Repos,Pk}$ and $VMT_{Repos,Ok}$ denote additional VMT due to repositioning trips during peak and off-peak periods, $MaaS_{i,\,Pk}$ and $MaaS_{i,\,Ok}$ represent number of MaaS trips originating from area type i during peak and off-peak periods, $Speed_{i,Pk}$ and $Speed_{i,Ok}$ are average speeds within area type i for peak and off-peak periods, and $PickUp_i$ is the pick-up wait time within the area type i.

The total VMT considering repositioning trips for MaaS mode can be calculated as follows:

$$VMT_{Total,Pk} = VMT_{Repos,Pk} + VMT_{Model,Pk} \tag{3-8}$$

$$VMT_{Total,Ok} = VMT_{Repos,Ok} + VMT_{Model,Ok} \tag{3-9}$$

where $VMT_{model,Pk}$ and $VMT_{model,Ok}$ denote model VMT estimates for peak and off-peak periods. The daily VMT is calculated as the sum of off-peak and peak periods VMTs as follows:

$$VMT_{Total,Daily} = VMT_{Total,Ok} + VMT_{Total,Pk} \tag{3-10}$$

3.6 Summary

The current version of the WF travel demand model is modified to estimate a range for VMT changes due to the use of SAVs. We designed three trip generation scenarios to investigate low-, medium-, and high-trip generation growth. We also developed four scenarios, namely base case, low, medium, and high penetration to examine the impact of MaaS market penetration on travel choices. Finally, 12 scenarios with different combinations of trip generation growth and MaaS market penetration are analyzed to estimate lower and upper bound for VMT increase in the study region for the 2040 projection year.

4. RESULTS AND FINDINGS

4.1 Overview

SAVs can potentially increase VMT in two ways: 1) by increasing trips from underserved populations; and 2) by converting modal trips to MaaS which can result in higher VMT when, for example, transit or nonmotorized trips are shifted, or, more likely, when additional VMT is generated during a MaaS vehicle being repositioned after passenger drop-off. We ran 12 scenarios of the WF travel model consisting of different combinations of trip growth rates and MaaS modal attractiveness. This experimental design allows us to estimate a range of VMT increase due to SAVs in the 2040 forecast year. **Figure 4.1** shows the scenario matrix.

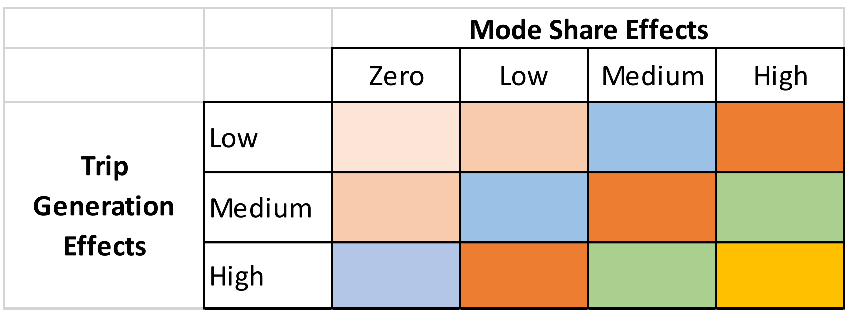

Figure 4.1: Experimental Design

The following sections present trip generation results, mode choice results and VMT estimation for these scenarios.

4.2 Trip Generation Results

Figure 4.2 illustrates the percentage of trip production increase due to the improved mobility of underserved populations for trip generation scenarios compared to the base scenario. Since the rates of work-based and school-based trips remain unchanged compared to the base scenario these trip purposes are intentionally excluded from the figure. Total number of trips increase by approximately 1%, 3.5%, and 7% for low-, medium-, and high-trip generation scenarios, respectively. Higher trip production increase is observed for HBShp and NHBNW trips compared to HBOth trip purposes. This is partially explained by the discretionary nature of HBShp and NHBNW trips, which makes these trips more sensitive to travel cost variation.

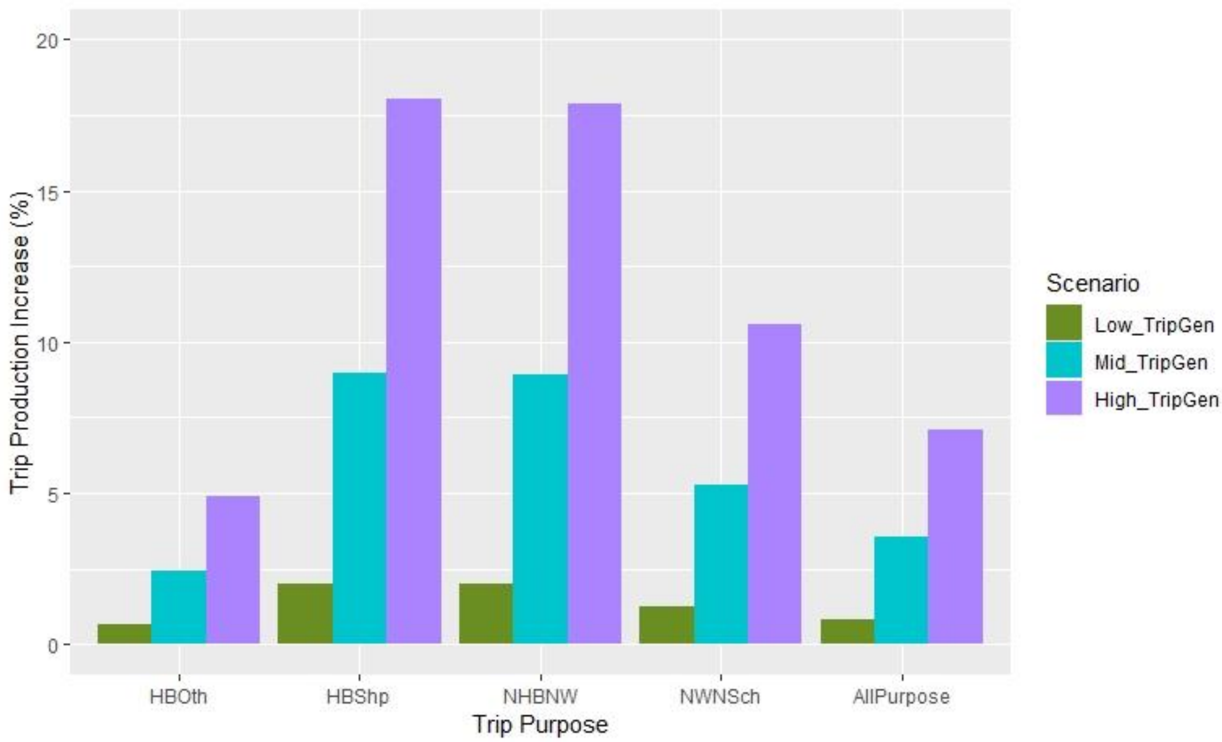

Figure 4.2 Designed Scenarios Trip Production Increase Compared to the Base Scenario

4.3 Mode Choice Results

Figure 4.3 illustrates daily mode shares across designed scenarios for all trip purposes. In the base scenario, the market split is Auto, Non-Motorized, and Transit (from high to low). The market share of shared ride modes (Auto_2Plus) is higher than non-shared ride mode (Auto_DriveAlone). This is partially explained by the unique demographics in Utah where there are larger average household sizes creating more shared ride trips, usually with family members. Therefore, many of the shared rides can be attributed to household members travelling together.

In those scenarios where the MaaS mode is available, the market split is Auto, MaaS, Non-Motorized, and Transit modes (from high to low). Auto_2Plus modes have higher shares than Auto_DriveAlone; similarly shared ride MaaS modes (MaaS 2Plus) have greater shares than non-shared MaaS mode (MaaS-RideAlone). Comparing the results of scenarios with MaaS available reveals that MaaS gains most of its share from Auto mode. However, there is still some shift from Non-Motorized and Transit modes to MaaS. It is also observed that shared ride MaaS modes attract more market shares from total modal shifts than non-shared MaaS mode. All else equal (i.e. not accounting for the VMT associated with SAV vehicle repositioning), this leads to an overall reduction in VMT for the forecast horizon year.

As expected, comparing MaaS mode share across scenarios with low-, medium-, and high-MaaS market attractiveness shows that reducing the generalized cost of MaaS (i.e. in-vehicle time, initial pick-up time, and operating cost) makes MaaS more competitive against conventional modes of transportation.

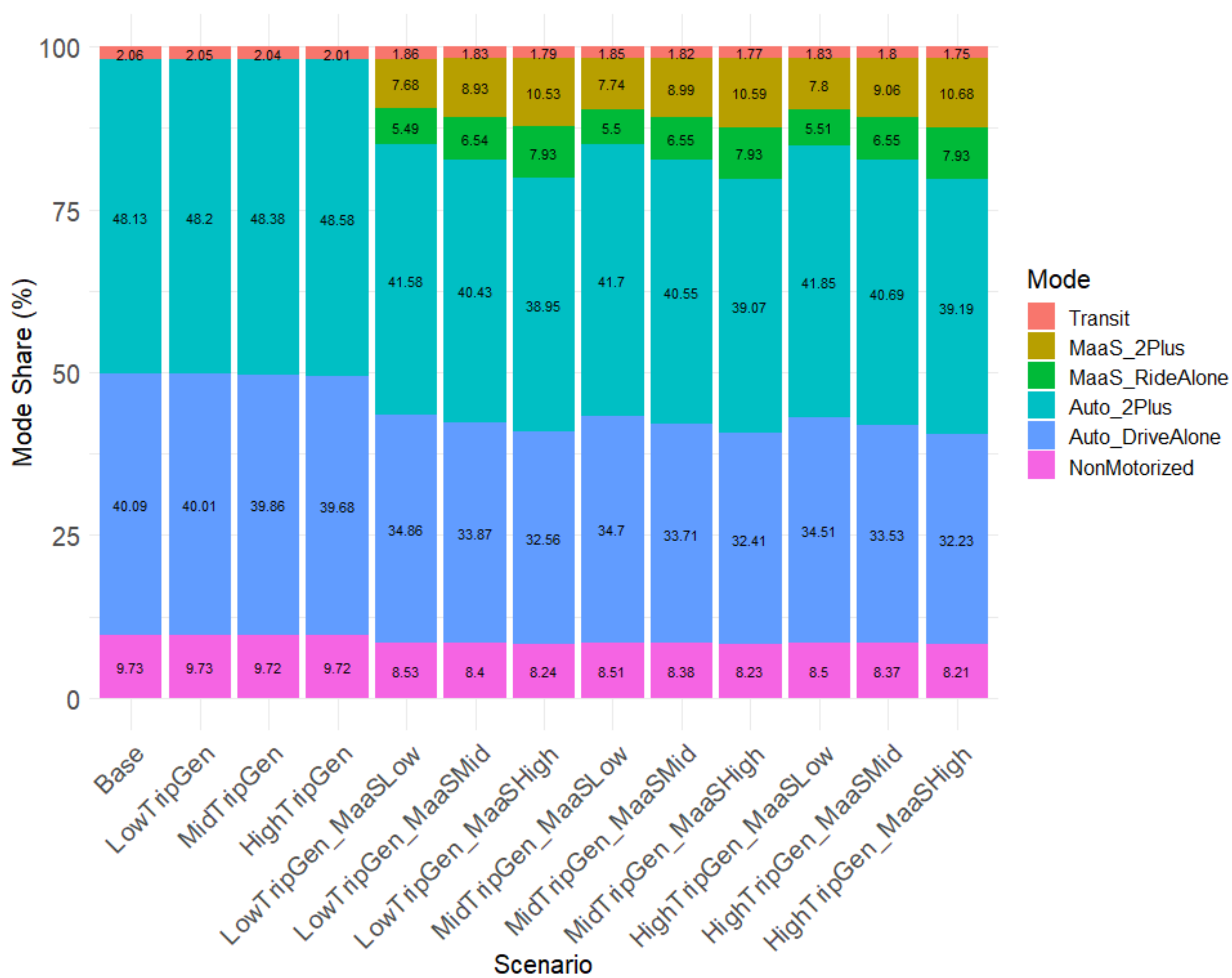

Figure 4.3 Daily Mode Split across Designed Scenarios

Figure 4.4 shows peak-period mode shares across different scenarios for all trip purposes, which exhibits a similar pattern to the mode shares across the entire day (Figure 4.3). However, there are smaller mode shares associated with shared rides compared to the daily results due to the higher percentage of work-based trips during peak-period which are mostly made by non-shared modes. As a result, the MaaS mode share is slightly smaller during peak period than for the entire day.

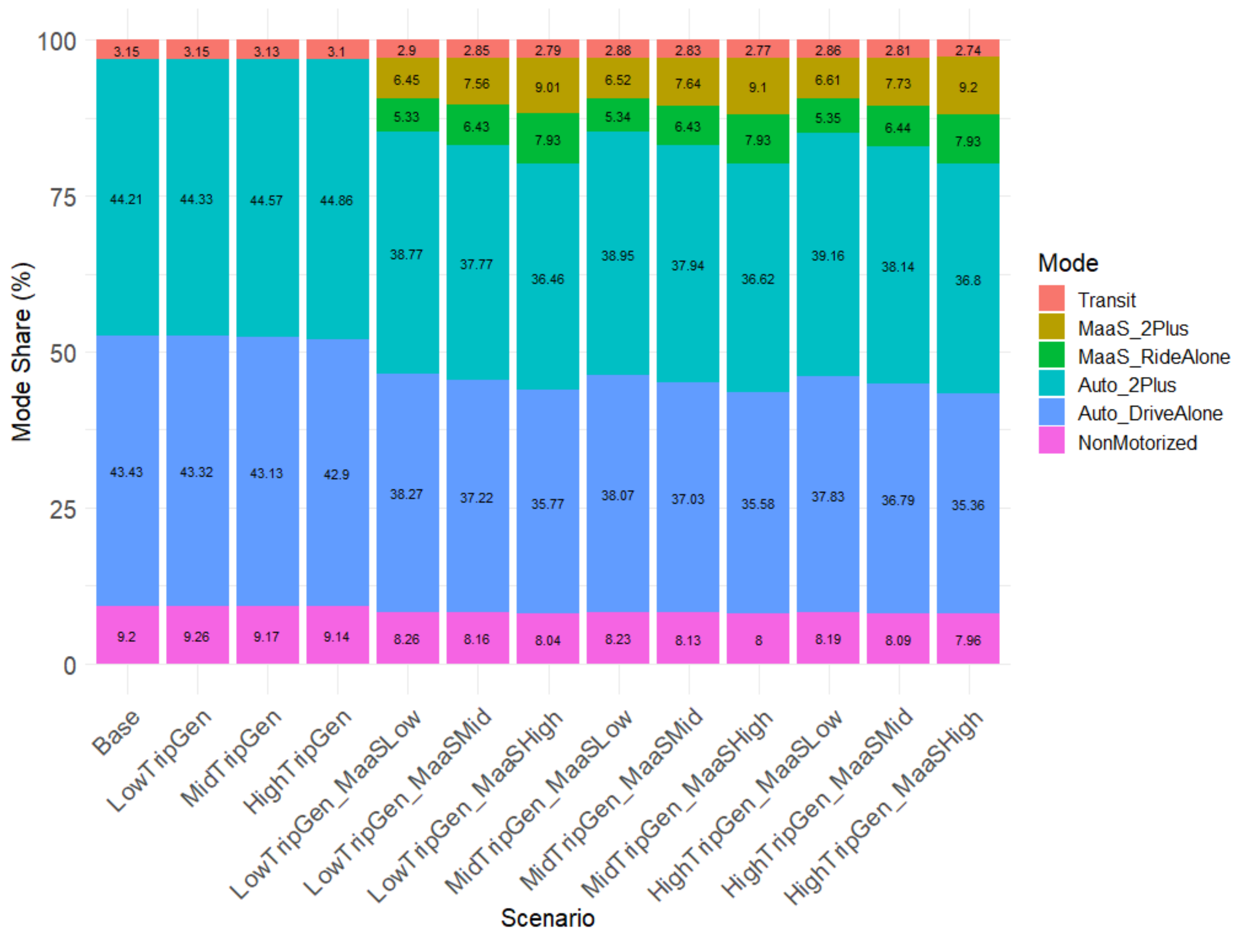

Figure 4.4 Peak-Period Mode Split across Designed Scenarios

Figure 4.5 illustrates the modal split by trip purpose across Base, MidTripGen_MaaSLow, and MidTripGen_MaaSHigh scenarios. It can be observed that there are more shared ride trips (including both MaaS and Auto) for NHB and HBO trips compared to other trip purposes. While the majority of HBO and NHB trips are made with Auto_2Plus modes, most of HBW trips are done with Auto_DriveAlone mode.

Figure 4.6 demonstrates modal shift by trip purpose from conventional transportation modes to MaaS. It is observed that for all trip purposes except NHB trips, MaaS competes more with Auto and Non-Motorized modes. For NHB trips, transit experiences the major market share loss to MaaS. Comparing modal shifts across different trip purposes shows that the Auto mode has dramatically lost its share to MaaS mode for HBO and NHB trips.

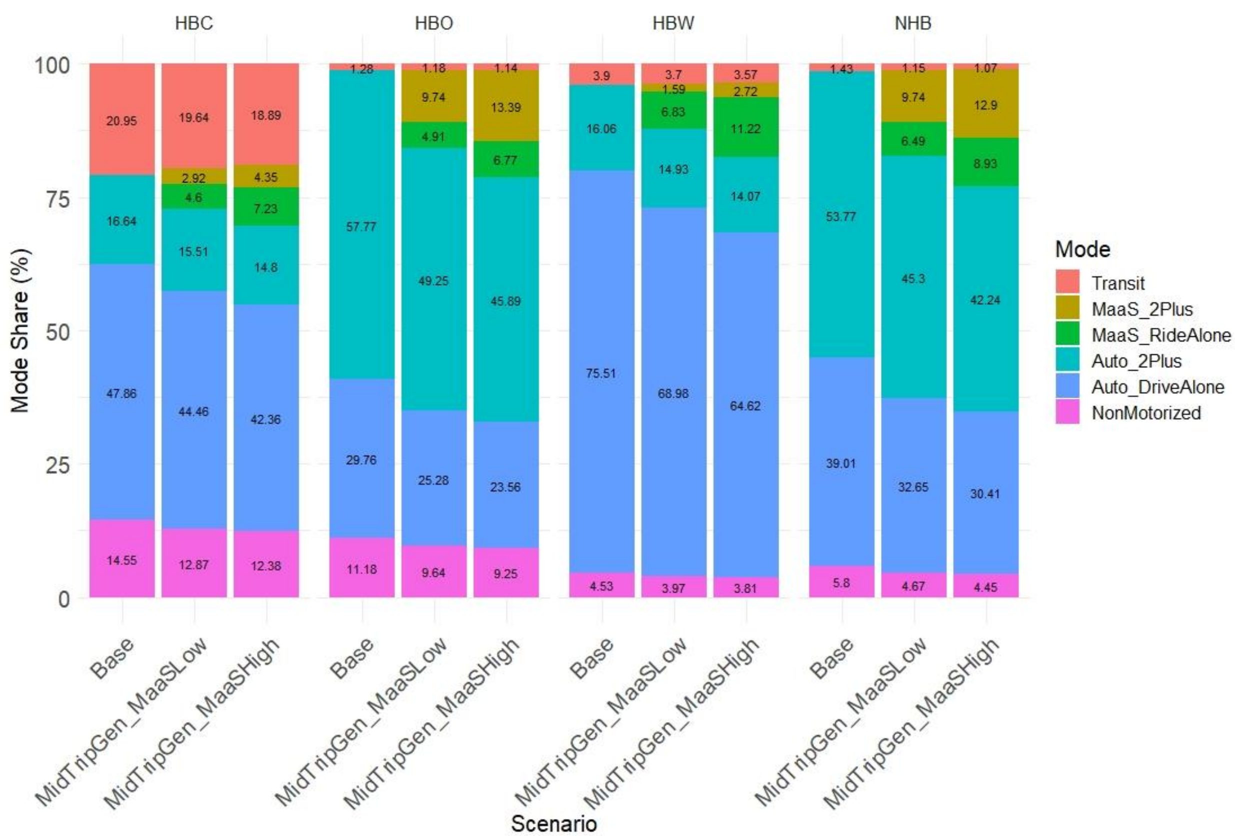

Figure 4.5 Daily Mode Split by Trip Purpose across Base, MidTripGen_MaaSLow, and MidTripGen_MaaSHigh

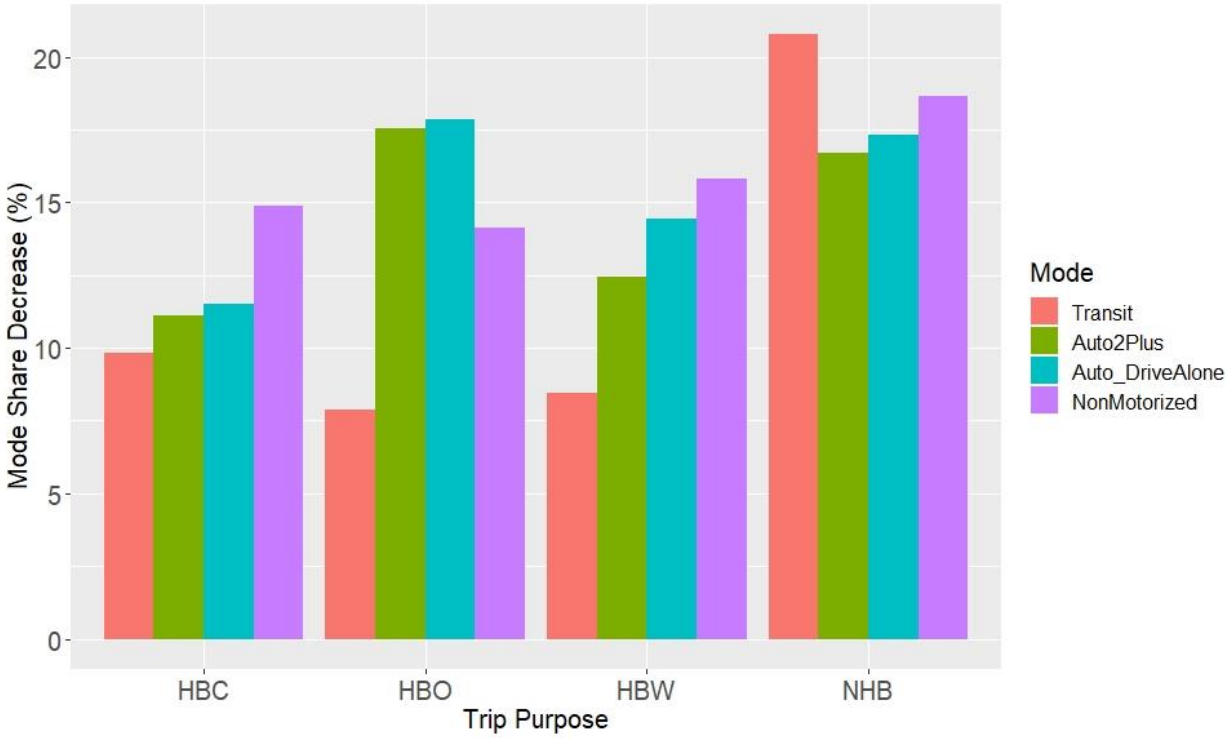

Figure 4.6 Modal Shift by Trip Purpose from Conventional Transportation Modes to MaaS Mode (MidTripGen_MaaSHigh scenario compared to the Base scenario)

Figure 4.7 shows the variation of transit modes shares across Base, MidTripGen_MaaSLow, and MidTripGen_MaaSHigh. For all trip purposes, the majority of transit trips are made by either Light Rail (LR) or Bus Rapid Transit (BRT). For HBW trips, Express Bus and Local Bus Rail modes have the lowest market shares. For HBC and HBO trips, Express Bus and Commuter Rail modes have the lowest shares. **Figure 4.8** illustrates the percentage of transit mode share reduction for MidTripGen_MaaSHigh scenario compared to the Base scenario. Across all trip purposes, Local Bus, BRT, and LR experience the main share loss to MaaS. Commuter Rail and Express Bus are maintaining most of their mode shares after MaaS's presence. It appears that MaaS competes more effectively with transit for shorter trips. This might be explained by the average shorter pick-up time for MaaS compared to transit.

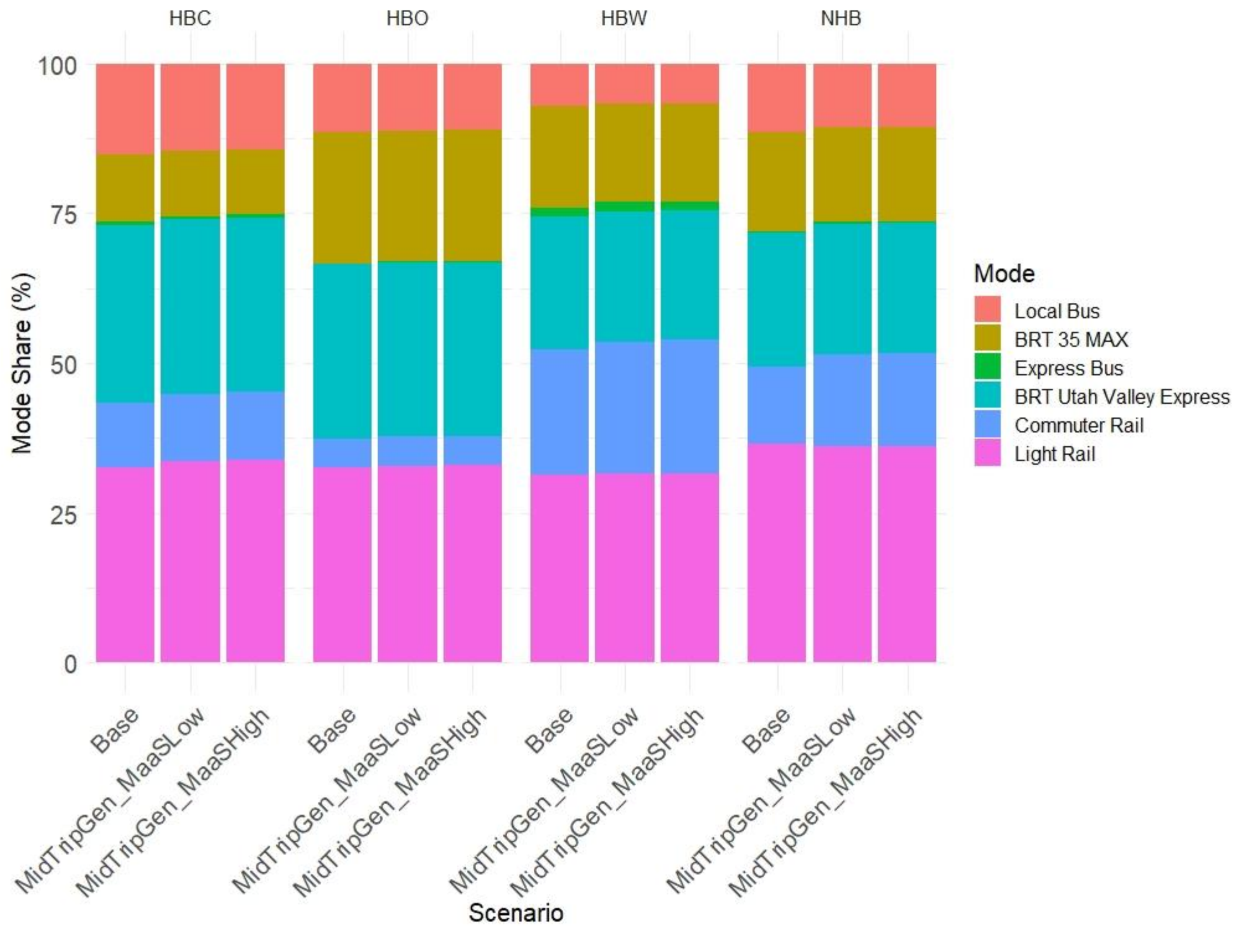

Figure 4.7 Daily Transit Mode Split by Trip Purpose across Base, MidTripGen_MaaSLow, and MidTripGen_MaaSHigh

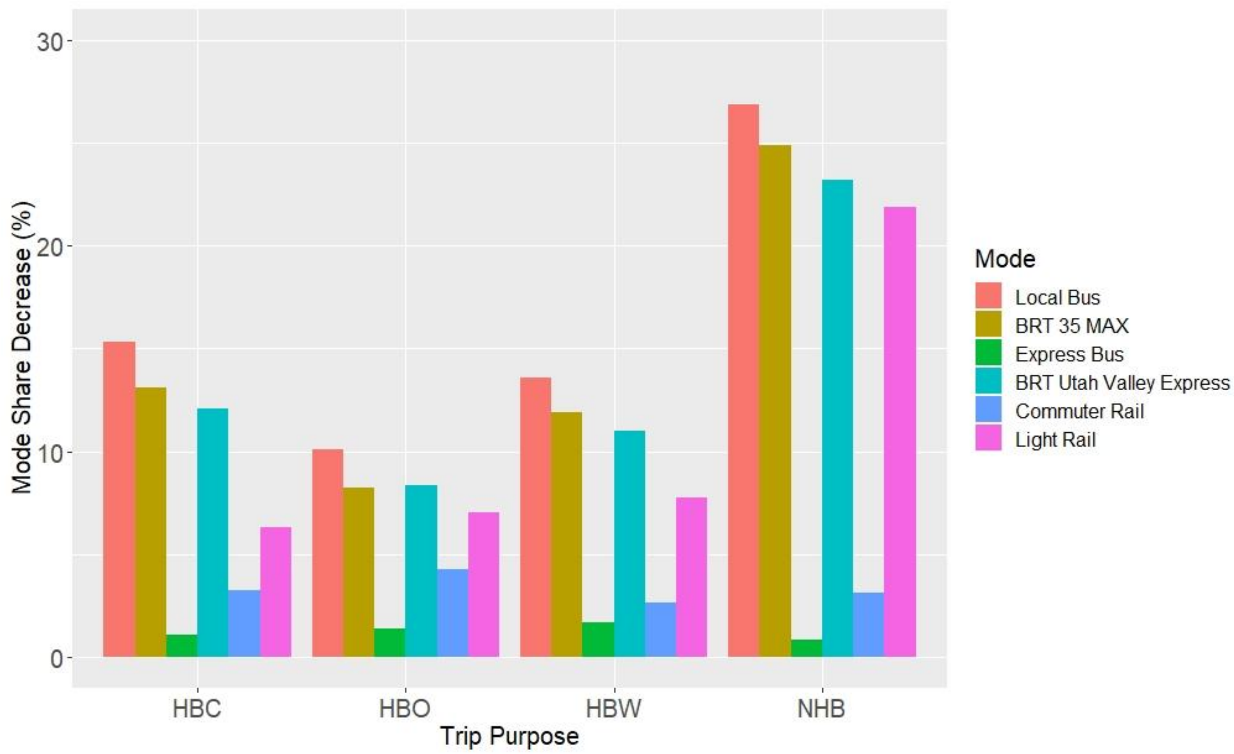

Figure 4.8 Daily Modal Shift by Trip Purpose from Transit to MaaS (MidTripGen_MaaSHigh Scenario Compared to the Base Scenario)

Figure 4.9 shows the peak-period mode split by trip length across High TripGen scenarios. The MaaS and Non-Motorized modes are more desirable for shorter trips than longer trips. Increasing the trip length is associated with significant share drop of MaaS and Non-Motorized modes and modal shift to various Auto modes. Comparing MaaS shares across scenarios with low, medium, and high MaaS penetration reveals that reducing MaaS cost significantly increases MaaS share for longer trips.

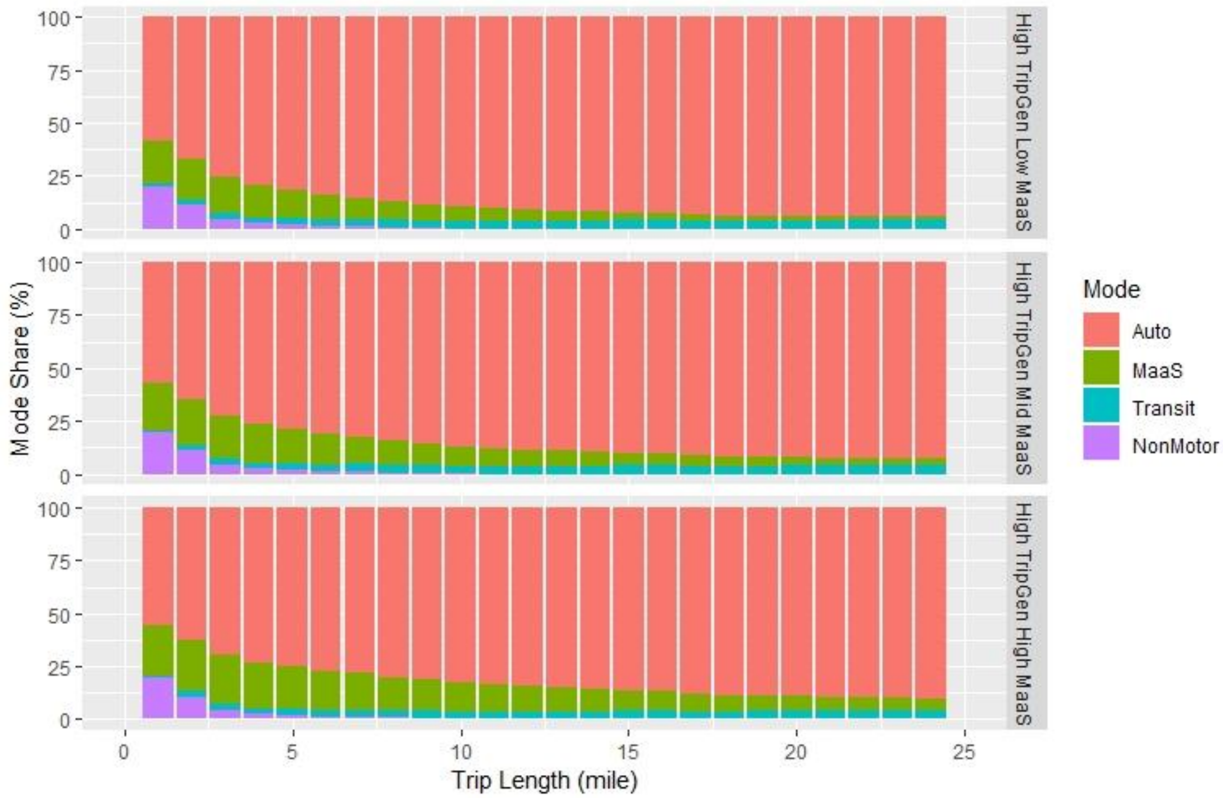

Figure 4.9 Peak-Period Mode Split by Trip Length for All HighTripGen Scenarios

4.4 VMT Results

Figure *4.10* shows the daily VMT before considering additional VMT due to repositioning trips across all scenarios. MaaS mode is not available in Base, LowTripGen, MidTripGen, and HighTripGen scenarios. Comparing VMTs of LowTripGen, MidTripGen, and HighTripGen scenarios with that of Base scenario shows the increase in daily VMT due to improved mobility of underserved populations as a result of the availability of AVs. As expected, the higher increase in trip rates are associated with greater increase in daily VMT.

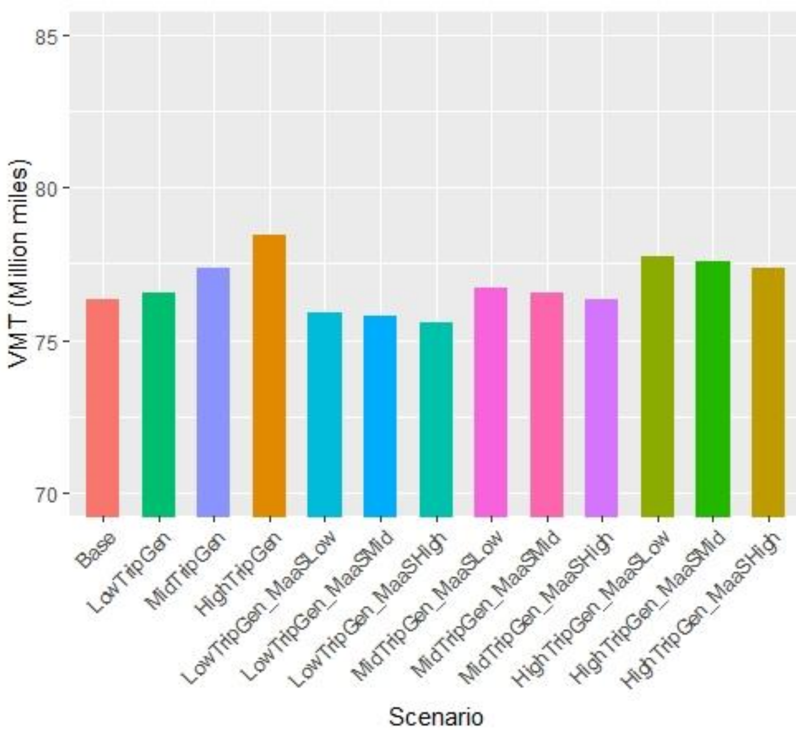

Figure 4.10 Daily VMT without Considering MaaS Repositioning Trips across Designed Scenarios

Introducing MaaS as a new mode to the mode choice model leads to a slight decrease in VMT for all scenarios with MaaS available (compared to the “zero” scenarios namely, LowTripGen, MidTripGen, and HighTripGen in Figure 4.1). This finding is partially explained by slightly higher modal shift to MaaS_2Plus modes than modal shift to MaaS_RideAlone. As discussed above, this finding relies in part on the unique demographics in Utah households and may not accurately account for additional factors discouraging a “pool” mode, such as discomfort in traveling with strangers. Given the current modeling framework, reducing the generalized cost of MaaS across scenarios to represent the low, medium, and high MaaS attractiveness, leads to a reduction in VMT largely due to the shift from drive alone to MaaS2+.

Additional daily VMT from trip repositioning is estimated for scenarios with the MaaS mode and added to the model-estimated VMT. **Figure 4.11** illustrates daily VMT considering the additional VMT due to repositioning trips. For the MaaS scenarios, significant VMT increase due to repositioning trips is observed. Moreover, higher MaaS penetration resulted in smaller VMT increase. This is because when MaaS is readily available, the repositioning trips would have shorter length (as the more distant passengers could be picked up by other MaaS). The daily VMT is estimated to increase in range of 4% to 9% across designed scenarios.

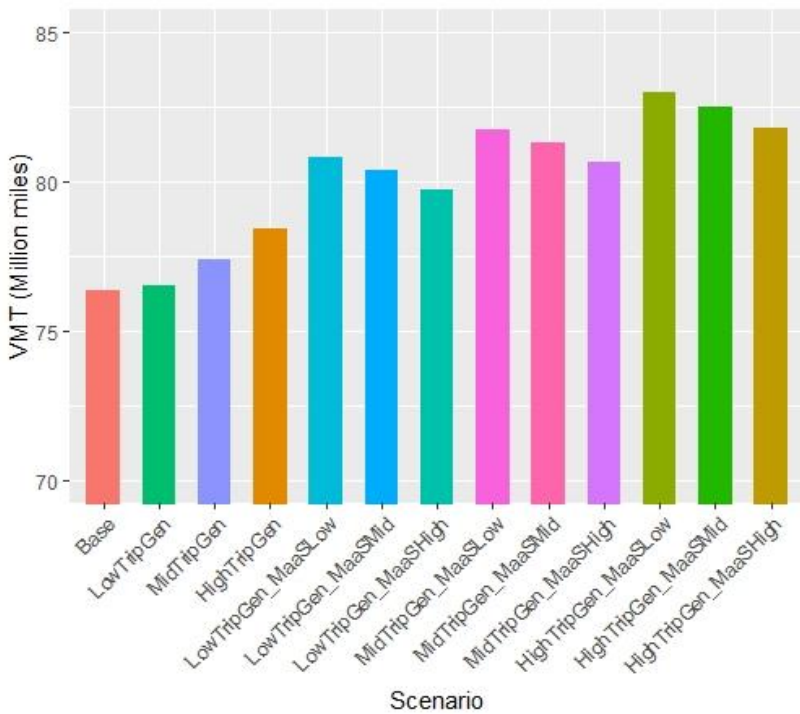

Figure 4.11: Daily VMT Considering MaaS Repositioning Trips across Designed Scenarios

4.5 Summary

In this research we analyzed the number of trips, modal shifts, and VMT with the introduction of SAVs into the regional model. Results revealed that SAVs can increase total number of trips up to 7% in the scenario with highest impact. Comparing modal splits across designed scenarios, it is showed that SAVs can cause modal shifts away from conventional transportation modes. Moreover, SAV can increase daily VMT up to 9% compared to the base scenario primarily due to the additional VMT incurred by repositioning trips.

5. CONCLUSION

5.1 Summary

In this research, we model the impact of SAVs on travel patterns in Utah in year 2040 forecast horizon. SAV is defined as the combination of AV technology with MaaS, which offers a new ridesharing option for travelers. We speculate that SAVs would have two major effects on transportation demand:

1. SAVs will increase the mobility of certain demographic populations, specifically households with children, households with elderly members, and people with mobility impairments.
2. SAVs represent a new mode – MaaS – that will offer new travel option, competing with the automobile, transit, and non-motorized modes.

We incorporated these effects by modifying trip generation and mode choice models of the WF Travel Demand Model. In the trip generation model, trip rates of households with children, elderly, and mobility-impaired members were increased to reflect the improved mobility that the AV technology provides. Overall, a range of 1-7% increase of trips has been estimated. In the mode choice model, a new mode - MaaS - is added, which competes for trips with the conventional modes – automobile, transit and non-motorized. Finally, 12 scenarios were designed to investigate different combinations of trip growth rates and MaaS market attractiveness. This experimental design allowed us to estimate a 4-9% range of VMT increase due to SAVs in the year 2040 forecast horizon.

5.2 Findings

Our results revealed that SAVs can increase the total number of trips by 1% to 7% across designed scenarios. Mode share comparison among scenarios showed that while MaaS can take market shares away from all conventional transportation modes, it competes more with auto and non-motorized modes. Reducing the generalized cost of MaaS makes the mode more appealing against conventional modes. Higher market shares were found for shared ride MaaS due in part to the larger household sizes in Utah. This finding, however, does not account for potential disbenefits of sharing a ride, such as discomfort in traveling with strangers.

Analysis of modal shift by trip purpose showed that for all trip purposes except NHB trips, SAVs compete more with auto and non-motorized modes. For NHB trips, transit experiences the largest mode shift to SAVs. Among available transit modes, Bus, BRT, and Light Rail are the ones that experience the most market share loss to MaaS.

Analyzing trip length distributions revealed that SAV mode is more desirable for shorter trips than longer ones. Moreover, while reducing generalized cost of SAVs makes the mode more competitive for longer trips, it does not significantly impact the share of SAVs for shorter trips. Lastly, it is observed that SAV increases daily VMT by 4% to 9% across designed scenarios due to both improved mobility of underserved population and additional VMT from the repositioning of vehicles towards the next rider.

5.3 Limitations and Challenges

In this study, several assumptions were made with regards to trip rate increase and the SAV utility function. In the future there is a need to verify these assumptions via survey data. SAVs can also promote public transport by providing first- and last- mile services reducing the extra time and hassle the travelers face going from their origin to the transit station and back. However, this research did not consider a combination of alternative transportation modes (e.g. SAV + transit) for trips. In addition, while SAV fleet size might have a significant impact on pick-up time, it is not considered in the modeling process.

Regarding repositioning trips, an offline post-processing analysis is performed to estimate the number and length of repositioning trips. Note that repositioning trips were not assigned to the network so their impacts on congestion and traffic flow are not assessed in the modeling process. While SAV also impacts roadway capacity and auto ownership, we ignored these impacts in our study.

We modeled the MaaS mode choice as MaaS Alone, MaaS2, and MaaS3+. Given how ridesharing decisions are currently being made (e.g. Uber and Lyft), a more appropriate modeling approach would be to include only two MaaS choices: MaaS Alone and MaaS Pool. This change may affect the attractiveness of MaaS Pool relative to how it was modeled in this research, leading to a slight change of results.

Additionally, security and safety concerns might present themselves due to SAV’s vulnerability to hacking and/or sharing a ride with strangers when there is no driver. Such impedance is not modeled in the study and future research could investigate the impacts of these factors on SAV attractiveness.

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